Curtin School of Allied Health

An Investigation of Pain Related Disability with Movement Quantity and Quality in Pre-Professional Dancers

Danica Hendry

ORCID ID: 0000 0001 8701 2212

This thesis is presented for the degree of
Doctor of Philosophy
of
Curtin University

September 2021

Notes on the *Print Edition*

This is the *Print Edition* of the thesis, optimised for physical printing and binding. It includes blank pages where needed to ensure new chapters, appendices and major front and back matter sections start on odd-numbered pages.

In contrast, the *Screen Edition* (the edition submitted electronically to Examiners and stored in online repositories) has no blank pages inserted, thereby facilitating a smoother on-screen reading experience.

Note that page numbers will differ slightly between the two editions. It is therefore recommended that any citations of this thesis should refer to page numbers in the more generally available *Screen Edition*.

Declaration

To the best of my knowledge and belief this thesis contains no material previously published by any other person except where due acknowledgment has been made.

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university.

Human Ethics

The research presented and reported in this thesis was conducted in accordance with the National Health and Medical Research Council National Statement on Ethical Conduct in Human Research (2007) – updated March 2014. The research studies received human research ethics approval from the Curtin University Human Research Ethics Committee (EC00262), Approval Numbers: HRE2017-0185 and HRE2017-0726.

Signature Redacted

Danica Hendry

30 August 2021

Abstract

Introduction

Pre-professional dancers commonly experience musculoskeletal pain, which can be disabling and distressing to the dancer. A contemporary view of pain development and management suggests that pain should be considered using a biopsychosocial perspective. In athletic populations, such as dancers, there has been a particular focus on the relationship between pain and a variety of movement parameters. However, quantifying these parameters within the context of daily training and performance remains a challenge. Movement parameters of particular interest can be broadly delineated into those that represent movement quantity and quality. Movement quantity has previously been tracked using schedules and activity diaries, which are both imprecise and biased. Activity monitors have been implemented to derive a general energy expenditure output, however it is increasingly recognised that quantifying movement specific loads is critical when understanding links with pain. For example, jumping and leg lifting tasks have frequently been cited as potentially provocative of pain. Further, we know from cross-sectional laboratory-based research that quality of movement factors, such as high ground reaction forces (GRF) during jumping tasks and the substantial range of hip elevation and lumbar spine sagittal angles that dancers use during leg lifting tasks may also be provocative of pain. Currently, no field-based system exists to track movement quality.

Recent developments in wearable sensor technology combined with computational approaches, such as machine learning, has allowed the potential for longitudinal research using serial, field-based measurement of specific movement quantity and quality variables. Machine learning models have been applied to wearable sensor data for the delineation of specific movement tasks in sports such as specific strokes in tennis, and tackles in rugby and Australian Rules football. While more limited, there are also examples of movement quality information, such as GRF and joint range of motion being output using machine learning applied to wearable sensor data during running. No researchers have applied machine learning methods to wearable sensor data for the objective quantification of movement quantity and quality in dancers. Additionally, while systems have been developed in other sporting areas, no researchers have applied the technology in a field-based study to explore the relationship between movement quantity and quality with athletes' pain.

The aims of this thesis were:

1. To develop and validate a field-based system capable of sufficiently accurate estimates of dance-specific movement quantity and the quality that these movements were executed (Study 1, 2A and 2B).
2. to determine if there was a relationship between dancers' movement quantity and quality with self-reported pain and pain related disability outcomes across a university semester (Study 3).

Methods, Results and Discussion

Study 1

Objective: To develop a human activity recognition system using wearable sensor data to accurately identify key ballet movements (jumping and lifting the leg). The primary objective was to determine if machine learning can accurately identify key ballet movements during dance training. The secondary objective was to determine the influence of the location and number of sensors on accuracy.

Methods: Pre-professional female dancers (n=23) were fitted with 6 Actigraph Link wearable sensors (100Hz). Dancers performed a series of discrete ballet movements; a series of different jumping and leg lifting tasks, followed by choreographed sequences. Dancers were simultaneously recorded on video (100fps). Activities were identified, classified and annotated frame-by-frame at 3 levels. Sensor and video data were time synchronised. Convolutional neural networks were applied to develop 2 models for each combination of six sensors (6, 5, 4, 3, etc.) with and without the inclusion of transition movements. The models were validated using leave one out cross validation to determine the degree of accuracy for each sensor combination.

Results: At the first level of classification, including data from all sensors, without transitions, the model performed with 97.8% accuracy. The degree of accuracy reduced at the second (83.0%) and third (75.1%) levels of classification. The degree of accuracy reduced with inclusion of transitions, reduction in the number of sensors and various sensor combinations.

Discussion: The models developed were robust enough to identify jumping and leg lifting tasks in real-world exposures in dancers. The system provides a novel method for measuring dancer training volume through quantification of specific movement tasks.

Such a system can be used to further understand the relationship between dancers' pain and training volume and for athlete monitoring systems. Further, this provides a proof of concept which could be translated to other lower limb dominant sporting activities.

Study 2A

Objective: To develop a wearable sensor system, using machine learning models, capable of accurately estimating peak GRF during ballet jumps in the field.

Methods: Female dancers (n = 30) performed a series of bilateral and unilateral ballet jumps. Dancers wore six ActiGraph Link wearable sensors (100 Hz). Data were collected simultaneously from two AMTI force platforms and synchronised with the ActiGraph data. Due to sensor hardware malfunctions and synchronisation issues, a multistage approach to model development, using a reduced data set, was taken. Using data from the 14 dancers with complete multi-sensor synchronised data, the best single sensor was determined. Subsequently, the best single sensor model was refined and validated using all available data for that sensor (23 dancers). Root mean square error (RMSE) in body weight (BW) and correlation coefficients (r) were used to assess the model GRF profile, and Bland-Altman plots were used to assess model peak GRF accuracy.

Results: The model based on sacrum data was the most accurate single sensor model (unilateral landings: RMSE = 0.24 BW, r = 0.95; bilateral landings: RMSE = 0.21 BW, r = 0.98) with the refined model still showing good accuracy (unilateral: RMSE = 0.42 BW, r = 0.80; bilateral: RMSE = 0.39 BW, r = 0.92).

Discussion: Machine learning models applied to wearable sensor data can provide a field-based system for GRF estimation during ballet jumps.

Study 2B

Objective: To develop a machine learning model to estimate thigh elevation and lumbar sagittal plane angles during ballet leg lifting tasks, using wearable sensor data.

Methods: Female dancers (n = 30) performed ballet-specific leg lifting tasks to the front, side and behind the body. Dancers wore six ActiGraph Link wearable sensors (100Hz). Data were simultaneously collected using an 18 Camera Vicon Motion Analysis System (250Hz). Due to synchronization and hardware malfunction issues, only 23 dancers had usable data. Using leave-one-out cross validation, machine learning models were compared with the optic motion capture system using root mean square error (RMSE) in

degrees and correlation coefficients (r) over the complete movement profile of each leg lift and mean absolute error (MAE) and Bland Altman plots for peak angle accuracy.

Results: The average RMSE for model estimation was 6.8° for thigh elevation angle and 5.6° for lumbar spine sagittal plane angle, with respective MAE of 6.3°and 5.7°. There was a strong correlation between the machine learning model and optic motion capture for peak angle values (thigh r = 0.86, lumbar r = 0.96).

Discussion: The models developed demonstrated an acceptable degree of accuracy for the estimation of thigh elevation angle and lumbar spine sagittal plane angle during dance-specific leg lifting tasks. This provides potential for a near-real-time, field-based measurement system.

Study 3

Objective: This field-based study aimed to determine the association between pre-professional student dancers' movement quantity and quality with (i) pain severity and (ii) pain related disability.

Methods: Pre-professional female dance students (n=52) participated in 4 time points of data collection over a 12-week university semester. At each timepoint dancers provided self-reported pain outcomes (Numerical Rating Scale as a measure of pain severity and Patient Specific Functional Scale as a measure of pain related disability) and wore a wearable sensor system. This system combined wearable sensors with previously developed machine learning models capable of capturing movement quantity and quality outcomes. A series of linear mixed models were applied to determine if there was an association between dancers' movement quantity and quality over the 4 time points with pain severity and pain related disability.

Results: Almost all dancers (n=50) experienced pain, and half of the dancers experienced disabling pain (n=26). Significant associations were evident for pain related disability and movement quantity and quality variables. Specifically, greater pain related disability was associated with more light activity, fewer leg lifts to the front, a shorter average duration of leg lifts to the front and fewer total leg lifts. Greater pain related disability was also associated with higher thigh elevation angles to the side. There was no evidence for associations between movement quantity and quality variables and pain severity.

Discussion: Despite a high prevalence of musculoskeletal pain, dancers' levels of pain severity and disability were generally low. Group level associations were identified between dancers' movement quantity and quality, and pain related disability. These findings may reflect dancers' adaptations to pain related disability, while they continue to dance. Further studies are required to understand this relationship, and the directional nature of the relationship, at an individual dancer's level. This proof-of-concept research provides a compelling model for future work exploring dancers' pain using field-based, serial data collection.

Conclusion

This doctoral thesis initially validated a novel, field-based approach to better understand the potential associations between movement and pain and it's associated disability in dancers. We developed a wearable sensor system which was capable of measuring dancers' movement quantity and quality of movement. The system combined a series of machine learning models developed using convolutional neural networks with a support vector machine and artificial neural networks to provide a comprehensive system capable of detecting the dance-specific jumping and leg lifting tasks. The system was also capable of estimating peak GRF during jumping and thigh elevation and lumbar spine sagittal angles during leg lifting tasks, with acceptable degrees of accuracy. The system was subsequently applied in a field-based study to explore the relationships between movement quantity and quality with pain severity and pain related disability. The results suggested some adaptation of dancers' movement when they experienced changes in levels of pain related disability. While previous work has suggested that dancers tend to "push through" pain and keep on dancing, this work highlights that when faced with disabling pain, while they continue to dance, they modify their movement quantity and quality. Through applying the novel measurement system developed in this research to a group of pre-professional dancers over the course of a university semester, we have presented a compelling model and a prospect for future work exploring dancer pain using field-based, serial data collection.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

AB	Adaptive Boosting
BW	Body weight
ANN	Artificial Neural Network
CART	Classification and regression tree
CNN	Convolutional Neural Network
DTW	Dynamic Time Warping
GRF	Ground reaction force
HCRF	Hidden Conditional Random Field
HMM	Hidden Markov Model
IMU	Inertial measurement unit
kNN	k-Nearest Neighbour
LCS	Longest Common Subsequence Algorithm
LR	Logistic Regression
LSTM	Long Short Term Memory
LSh	Left shin
LTh	Left thigh
MAE	Mean absolute error
MLP	Multi Layer Perceptrons
NB	Naïve Bayesian
NN	Neural Network
NRS	Numerical Rating Scale
PART	Partial decision tree
PSFS	Patient Specific Functional Scale
r	Correlation coefficient
RF	Random Forrest
RMSE	Root mean square error
RPE	Rating of perceived exertion
RSh	Right shin
RTh	Right thigh

SD	Standard deviation
SEFIP	Self Estimated Functional Inability due to Pain
SVM	Support Vector Machine
Sx	Sacrum
Tx	Thoracic
VOTE	Vote Classifier

List of Publications and Research Outputs

Multiple aspects of this thesis have been published in peer-reviewed journals and presented at scientific conferences, as listed below. Additionally, several presentations have received awards.

Publications

Chapter 3

Hendry, D., Chai, K., Campbell, A., Hopper, L., O'Sullivan, P. & Straker, L. (2020) Development of a human activity recognition system for ballet tasks. *Sports Med Open*, *6*, 20, doi: https://doi.org/10.1186/s40798-020-0237-5

Chapter 4

Hendry, D., Leadbetter R., Mckee, K., Hopper, L., Wild, C., O'Sullivan, P., Straker, L. & Campbell, A. (2020) An exploration of machine learning estimation of ground reaction force from wearable sensor data. *Sensors, 20*(3), 740. doi: https://doi.org/10.3390/s20030740

Chapter 5

Hendry, D., Napier, K., Hosking, R., Chai, K., Davey, P., Hopper, L., Wild, C., O'Sullivan, P., Straker, L., & Campbell, A. (2021) Development of a machine learning model for the estimation of hip and lumbar angles in ballet dancers. *Med Probl Perform Art, 36*(2): 61-71. doi: https://doi.org/10.21091/mppa.2021.2009

Appendix O

Hendry, D., Straker, L., Campbell, A., Hopper, L., Tunks, R., & O'Sullivan, P. (2019). An exploration of pre-professional dancers' beliefs of the low back and dance-specific low back movements. *Med Probl Perform Art, 34*(3), 147-153. doi: https://doi.org/10.21091/mppa.2019.3025

Submissions

Chapter 6

Hendry, D, Campbell, A., Smith, A., Hopper, L., Straker, L. & O'Sullivan, P. Movement quantity and quality: How do they relate to pain and disability in dancers. Submitted to PlosOne

Presentations

Invited Speaker Presentations

International Association of Biomechanics and American Society of Biomechanics Conference 2019, Calgary, Canada

Validation of a wearable sensor system to capture magnitude and quality of dance movements

Curtin Institute for Computation Research Symposium 2019, Perth, Western Australia

Development of human activity recognition and kinematic estimation models, for measurement of dancers' movement quantity and quality

Oral Presentations

Mark Liveris Research Symposium 2018, Perth, Australia

Development of a wearable sensor system for training volume quantification in ballet

Sports Medicine Australia Conference 2018, Perth, Australia

Development of a wearable sensor system for training volume quantification in ballet.

Pre-professional dancer; beliefs about the lower back and perceptions of safety during dance movements

Australian Society for Performing Artists Health Conference 2018, Sydney, Australia

The development of a wearable sensor system to quantify training volume in ballet

An exploration of pre-prfessional dancers beliefs of the lumbar spine and lumbar spine functional movements

Curtin University, Physiotherapy and Exercise Science Emerging Research Conference 2020, Online

Development of human activity recognition and kinematic estimation models, for measurement of dancers' movement quantity and quality

Awards and Prizes

- Best oral presentation Mark Liveris Research Symposium, Curtin University, 2018: Awarded for presentation on findings from Study 1
- Runner Up 3 Minute Thesis Competition, Curtin University, 2018: Awarded for presentation of overview of methodology of entire thesis
- Career Development Award Australian Society for Performing Artists Health Conference, 2018: Awarded for presentation on findings from Study 1
- West Australian semi finalist FameLab 2019: Awarded for presentation of overview of methodology of entire thesis

Acknowledgements

Often when people speak of their PhD, they express how difficult it was, and how they have felt very alone and overwhelmed in their journey. I am grateful that this was not the case for me. My PhD journey, while challenging at times, has been exciting and enjoyable. Professionally, I have been fulfilled with a sense of accomplishment as I have grown in my research career, alongside a stimulating clinical and teaching career. Perhaps appropriately, substantial parts of this thesis were written in dressing rooms of theatres across Australia while working as the physiotherapist on ballet and musical theatre productions. On a personal level, within the time of my PhD, I have married my best friend and become a mother. The balance I have managed to find throughout my PhD has been supported by an incredible team of people, and for that I am grateful.

Firstly, I would like to say a huge thank you to my supervisors, Amity Campbell, Leon Straker and Peter O'Sullivan. All of you have gone above and beyond in supporting my growth throughout this PhD. Thank you for supporting my research interests and guiding me in the development and implementation of this research. The amount of time and energy that you have invested into this project has been enormous. Thanks for allowing the flexibility to continue to grow in other areas of life while embarking on this journey, and for encouraging a sense of work life balance. I am thankful to have had the opportunity to work with such inspiring mentors.

This project was a collaboration between researchers within the Curtin School of Allied Health, Curtin Institute for Computation, Curtin School of Engineering and Western Australian Academy of Performing Arts (WAAPA). Thank you to all of the people who came on for different parts of this research project. In particular, thank you to Kevin Chai, Kathryn Napier, Richard Hosking and Ryan Leadbetter for all of your expertise in machine learning. Additionally, to Anne Smith for your guidance in statistical analysis and Paul Davey for the development of Labview programs for data processing. Thanks also to Luke Hopper for the facilitation of participant recruitment at WAAPA and to all of the dancers who participated in this research.

Finally, to the PhD students who I have shared this journey with, thank you all for the support and friendship. While the journey has been a positive one for me, it has not come without it's hurdles. These have been easier to overcome with your support.

To my incredible family

In particular my husband Jack, my baby girl Poppy, Mum and Dad. Thank you for encouraging me to embark on this journey, and then for standing by me and providing unconditional love and support throughout it. From celebrating the highs, to facing the challenges head on, this has been your journey too, so thanks for embracing it with me.

Chapter One

1

Introduction

This chapter provides an overview of the background and structure of this doctoral thesis. It begins by providing a brief background to the thesis, before stating the problem that this thesis is aiming to address. It highlights the primary aims of the thesis and provides a brief summary of each chapter and appendix.

1.1 Background

Dance is considered a valued activity to both dancers and audiences alike. Results of the AusPlay survey demonstrated that dance is the fourth most popular organised, out of school sport / physical activity for children under the age of 14, with an overall participation rate of 8.9% in Australia (Australian Sports Commission, 2021). Further, it is the second most popular sport / physical activity for girls in Australia, and female participation peaks at 5-8 years old (participation rate 22.8%) before dropping in subsequent years (Australian Sports Commission, 2021). By the time female dancers are aged 15-17 years old participation rates drop to 6.8% and by early adulthood (18-24 years old) rates drop to 2.4% (Australian Sports Commission, 2021). These late adolescent / early adulthood ages are typically when dancers who are considering a professional pathway in dance transition into pre-professional dance programs, such as university dance programs, with the potential to have a professional career. This is particularly true for ballet and contemporary dance. While multiple dance styles exist and are enjoyed by many, ballet and contemporary dance are most commonly the focus of pre-professional dance programs in Australia.

Pre-professional dance training is characterised by a substantial increase in training loads from recreational dance loads, during a time when dancers' bodies are continuing to develop, which may relate to the development of musculoskeletal pain and disability (Fuller, Moyle, Hunt, & Minett, 2019). Indeed, systematic reviews have suggested that dancers' musculoskeletal pain and pain related disability is prevalent during transition into pre-professional training, and throughout dancers' pre-professional years, with the majority of dancers experiencing pain at some point within their dance training (Fuller et al., 2019; Hamilton, Hamilton, Warren, Keller, & Molnar, 1997; Negus, Hopper, & Briffa, 2005). The lower limb and lower back are the most common regions affected, with pain commonly suggested to be related to "overuse" (P. J. Smith et al., 2015). Within the dance literature, painful events are most commonly described as "injury" (P. J. Smith et al., 2015; T. O. Smith et al., 2016). However, there is a lack of consensus on the definition of "injury" and the construct of "injury" may not adequately reflect the true underlying basis of musculoskeletal pain in dancers, as identifiable tissue damage is often not present with many musculoskeletal pain presentations (Caneiro et al., 2021). Therefore, within this thesis broader concepts of pain and pain related disability will be the focus. However to accurately reflect the published literature, when a publication refers to "injury" the authors' definition of "injury" has been included.

The impact of pain on dancers can be substantial, resulting in reduced training, more mental health issues and increased dancer attrition (Hamilton et al., 1997; Mainwaring &

Finney, 2017). Pain related disability is seen as the leading cause of attrition from dance training (Hamilton et al., 1997). Further, dancers with a history of pain related disability have reported increased generalized and performance anxiety and have rated psychological distress levels as high (Mainwaring & Finney, 2017). Gaining a deeper understanding of factors related to the development of pain related disability during dancers' pre-professional years would provide an opportunity for targeted management of pain related disability during this time.

Contemporary understanding of musculoskeletal pain development is complex and needs to include variables from a broad biopsychosocial perspective (O'Sullivan et al., 2018). There have been a number of studies that have identified a range of biopsychosocial risk factors for pain related disability in dancers (Cahalan, Bargary, & O'Sullivan, 2018; Cahalan, Bargary, & O'Sullivan, 2019; Cahalan et al., 2016; Kenny, Whittaker, & Emery, 2016). These include psychological factors such as dancers' coping skills, negative psychological distress, perfectionism and mood states as well as a range of physical factors including anthropometrics, biomechanics and training loads (Kenny et al., 2016). Given the physical nature of dancers' daily training, particular research attention has been brought to the domain of physical factors. Within this domain, the majority of research has focussed on dancers' overall training volume (Boeding, Visser, Meuffels, & de Vos, 2019; Cahalan et al., 2019; Cahalan, Kearney, et al., 2018; Jeffries et al., 2020; L. Lee, Reid, Cadwell, & Palmer, 2017; Shaw et al., 2021; Volkova & Kenny, 2020). However more recently researchers have recognised that overall training volume, while useful, does not provide sufficient insight into the complete training demands that may be associated with the development of pain and pain related disability (Murphy, Glasgow, & Mosler, 2021). As a result there is growing interest in more detailed movement quantity (for example, gross activity / movement counts) and quality (for example, detailed biomechanics, such as landing force) (Murphy et al., 2021). There are no reported studies identified within dance that explore the relationship of movement quantity and quality with pain and pain related disability.

Within the last 10 years there has been substantial interest in the relationship between movement quantity and pain development in athletes more broadly (Gabbett, 2016, 2020a; Gabbett, Hulin, Blanch, & Whiteley, 2016; Gabbett, Whyte, Hartwig, Wescombe, & Naughton, 2014). However, within the dance literature this area of research remains in its infancy. While there is a growing interest in capturing dancers' training volume as a measure of movement quantity, the current body of literature largely relies on dancers' schedules and their subjective reporting of their training hours (Boeding et al., 2019; Cahalan et al., 2019; Cahalan, Kearney, et al., 2018; Jeffries et al., 2020; Volkova & Kenny, 2020) These measures are both imprecise and potentially biased. Recently, researchers have started using accelerometry to capture dancers' movement quantity, using data processing methods such as vector magnitude and time spent at different physical activity intensities as measures of cumulative movement quantity (Jeffries, Wallace, & Coutts, 2016; Kozai, Twitchett, Morgan, & Wyon, 2020). Additionally, reserachers have applied session rating of perceived exerction (RPE) to quantify workloads, providing measure of the burden of workload on the dancer (Boeding et al., 2019; Jeffries et al., 2016; Jeffries et al., 2020). While these methods provide more objective quantification of dancers' movement quantity, and the impact this movement quantity has on the dancer, they only provide an indication of overall workload and do not account for the specific movements that may be provocative of pain and disability in dancers, such as jumping and leg lifting tasks. While it is recognised that quantifying movement specific loads is critical when understanding links with pain, currently no field-based systems capable of objectively quantifying dance-specific movements exist.

Jumping and leg lifting tasks have commonly been suggested as being associated with musculoskeletal pain and pain related disability in dancers (Mattiussi et al., 2021; Mattiussi et al., 2021; C. Swain, Bradshaw, Whyte, & Ekegren, 2018; Vassallo, Hillier, Pappas, & Stamatakis, 2017). As well as the quantity of these movements being potentially provocative, researchers have hypothesised that the quality of movement seen during these tasks may also relate to pain and disability, however the direction of this relationship remains unclear (Mattiussi et al., 2021). Quality of movement refers to the specific biomechanical features of movement which could include aspects such as forces, acclerations, range of movement and variability (Fietzer, Chang, & Kulig, 2012; Gorwa, Dworak, Michnik, & Jurkojc, 2014; Peng, Chen, Kernozek, Kim, & Song, 2015). For example, the large ground reaction forces (GRFs) that dancers display during repeated jumping is thought to contribute to the development of lower limb pain (Fietzer et al., 2012; Gorwa, Michnik, Nowakowska-Lipiec, Jurkojć, & Jochymczyk-Woźniak, 2019; Peng et al., 2015). Cross-sectional, laboratory-based studies have demonstrated that dancers with knee pain land with higher peak GRF than those without pain (Fietzer et al., 2012; Peng et al., 2015). Researchers and clinicians also commonly believe that the large ranges of hip and lumbar spine movement that dancers employ during leg lifting tasks may relate to the development of hip and low back pain (Biernacki, d'Hemecourt, Stracciolini, Owen, & Sugimoto, 2020; Biernacki et al., 2018; Bronner, 2012; Bronner & Ojofeitimi, 2011; Swain et al., 2018). However, while laboratory-based set ups have been used to measure the range of motion dancers achieve during leg lifting tasks (Bronner, 2012; Bronner & Ojofeitimi, 2011), no research has formally evaluated the relationship between these movement parameters and pain. While laboratory-based measurement systems are considered gold standard for the measurement of GRF and range of motion, they have low ecological validity, not allowing for capture of the large range of different jumping and leg lifting movments that a dancer performs in their normal training, and may not be appropriate for repeated monitoring (Lara & Labrador, 2013).

Recent developments in wearable sensor technology combined with advanced computational approaches, such as machine learning, have allowed the potential for longitudinal research using serial, field-based measurement of specific movement quantity and quality variables (Cust, Sweeting, Ball, & Robertson, 2019; Demrozi, Pravadelli, Bihorac, & Rashidi, 2020; Lara & Labrador, 2013). Machine learning is a branch of artificial intelligence where models and algorithms undergo "training" using raw data with criterion information, to then predict the response, and have been shown to perform better than simple algorithms for some complex problems (Cust et al., 2019). Within sport, machine learning has been applied to wearable sensors to recognise sport-specific movement tasks, such as tackles in rugby, specific strokes in tennis and hits in volleyball, allowing for the potential of automated, field-based movement quantity measurement (Cust et al., 2019). Additionally, machine learning applied to wearable sensor data has been used to estimate movement quality variables such as GRFs and joint range of motion during running (Wouda et al., 2018). There appears to be no published applications of machine learning to wearable sensor data for the measurement of movement quantity and quality in dance. Additionally, while the aforementioned systems have been developed for field-based use (Cust et al., 2019; Wouda et al., 2018), there are no published studies of their use within the field. Interestingly, while previous work has described the development of machine learning models, no reports of the application of these models in field-based studies to explore the relationship between movement parameters and pain have been published. Considered together, the results of these studies suggest the potential for the development of a wearable sensor system that can measure dance-specific movement quantity and quality. The development of such a system would allow for longitudinal, field-based research, exploring associations between physical factors and pain and pain related disability.

1.2 Statement of the problem

Pain and pain related disability is common in pre-professional dancers. While movement quantity and quality are thought to be associated with pain and disability in dancers there is limited evidence to support these claims. The evidence that exists is limited to subjective, and potentially biased, reporting of movement quantity and to cross-sectional laboratory-based studies of movement quality, with low ecological validity. To better understand the relationship of dancers' movement parameters with pain and disability, the development of an accurate field-based system to measure dancers' movement quantity and quality is required. This system subsequently needs to be applied to a sample of dancers to allow for determination of associations of movement quantity and quality with dancers' pain.

1.3 Thesis aims

This thesis presents a series of 3 studies. The first 2 studies were cross-sectional validation studies, the first field-based where data was collected in a dance studio, the second laboratory-based. The third was a longitudinal field-based study. The aims of the thesis were:

1. To develop and validate a field-based system capable of sufficiently accurate estimates of dance-specific movement quantity and the quality that these movements were executed (Study 1, 2A and 2B).

2. to determine if there was a relationship of dancers' movement quantity and quality with self-reported pain and pain related disability outcomes across a 12-week period (Study 3).

1.4 Structure of the thesis

This thesis comprises 7 chapters and a series of appendices. The thesis will describe three studies.

Chapter 1 provides an introductory overview of the problem that is the high prevalence of pain amongst pre-professional dancers, it's relationship with movement quantity and quality and the limitations in the current measurement systems and how machine learning applied to wearable senor data may assist in overcoming these limitations.

Chapter 2 provides a review and synthesis of the scientific literature associated with this body of work, beginning with the prevalence and impact of musculoskeletal pain and pain related disability in dance. It will provide review of the current literature regarding the association of movement quantity and quality with pain related disability, describing how movement quantity and quality is measured in dancers and how these factors relate with pain / pain related disability in dance, inclusive of specific movements that may be provocative of pain and pain related disability. The current scope of the use of wearable sensor technology within dance and the application of machine learning methods to wearable sensor data to allow for the objective quantification of movement quantity and quality will be reviewed. The chapter concludes by summarising the gaps in the literature.

Chapter 3 describes the development and validation of a machine learning and wearable sensor human activity recognition system for dance-specific movement tasks (jumping and leg lifting), allowing for field-based measurement of movement quantity. This study was published in *Sports Medicine Open*.

Chapter 4 describes the development and validation of machine learning models for the estimation of GRFs during dance-specific jumping activities, for field-based measurement of movement quality. This study was published in *Sensors.*

Chapter 5 describes the development and validation of machine learning models for the estimation of thigh elevation angles and lumbar spine sagittal plane angles during dance-specific leg lifting activities, for field-based measurement of movement quality. This study was published in *Medical Problems of Performing Artists*.

Chapter 6 presents a field-based study in which repeated wearable sensor-based measures of movement quantity and quality (measured using the machine learning models described above), along with self-reported measures of pain and disability were collected at 4 time points across a 12-week period, in the lead up to and following a performance season. This study has been submitted to a journal and is under review.

Chapter 7 presents the discussion of the main findings of the thesis, detailing what this study adds to existing methods for measuring quantity and quality of movement in dance and how movement quantity and quality are related with pain and pain related disability in dancers. Challenges of the development and application of the wearable sensor system will be described, with specific focus towards learnings from this body of work for application in future directions for research and clinical use.

Appendices A to N present ethical approval, recruitment materials, participant information and consent forms, questionnaires used and additional information for each study.

Appendix O presents a parallel study that aimed to further explore some other factors that relate to dancers' pain. This was a cross-sectional study that evaluated dancers' beliefs surrounding low back pain and dance-specific movements. This study has been published in *Medical Problems of Performing Artists.*

Appendices P and Q presents statements of contribution from all authors and copyright permissions from journals where manuscripts have been published.

Chapter Two

2

Literature Review

This chapter aims to review the current scientific literature and identify the gaps in the literature regarding: 1) the prevalence and burden of musculoskeletal pain and pain related disability in dance, 2) how movement quantity is measured in dancers and how it relates with pain / pain related disability in dance, 3) the specific movements that dancers perform which may relate with pain / pain related disability, 4) how movement quality is measured in dancers and how it relates with pain / pain related disability in dance, 5) the current scope of the use of wearable sensor technology within dance and 6) the application of machine learning methods to wearable sensor data to allow for the objective quantification of movement quantity and quality. Within the dance literature, painful events are most commonly described as "injury". Limitations of this term will be highlighted and within this research the focus will be on broader concepts of pain and pain related disability. However, to accurately reflect the published literature, when a publication refers to "injury" this term is utilised and the authors' "injury" definition is included.

2.1 Prevalence and burden of pain and pain related disability in dance

Dance is a popular and valued industry in Australia and internationally. On stage, professional dancers wow audiences with athleticism, artistry and grace. However, in the quest to achieve this, dancers embark on a journey of demanding training volumes, often accompanied by periods of musculoskeletal pain and / or pain related disability. The majority of dance medicine literature describing painful events has used the term “injury”. However ‘injury’ implies evidence of anatomical level tissue damage (Liederbach, Hagins, Gamboa, & Welsh, 2012) yet pain does not necessarily correlate well with radiological evidence of tissue damage (Caneiro et al., 2021; Kulig, Loudon, Popovich, Pollard, & Winder, 2011; Kulig, Oki, Chang, & Bashford, 2014; Mayes, Ferris, Smith, Garnham, & Cook, 2016a, 2016b, 2016c, 2016d; Suri, Boyko, Goldberg, Forsberg, & Jarvik, 2014). For example, in dancers, radiological evidence of hip morphological and pathological changes (Mayes et al., 2016a, 2016b, 2016c, 2016d), and lower limb tendinopathic changes have not correlated with the presence of pain nor with pain related disability (Comin et al., 2013; Kulig et al., 2014). Therefore, there is a need to understand musculoskeletal pain outside of the currently used injury model. Another problem with many injury definitions is the requirement for the seeking of medical attention and / or a time period of absence from dance related activity (Comin et al., 2013; Ekegren, Quested, & Brodrick, 2014; Kenny, Palacios-Derflingher, Whittaker, & Emery, 2018; Liederbach, Dilgen, & Rose, 2008; Winston, Awan, Cassidy, & Bleakney). Medical attention definitions may not be appropriate in the context of pre-professional dance, as dancers do not always have access to on-site physiotherapy or are often slow to seek help when experiencing musculoskeletal “injury” (Kenny et al., 2018). This is potentially because a) they believe they can manage the pain themselves, b) they do not want to bring attention to the problem because of any potential negative implications it may bring, or c) a lack of trust that the medical professional may lack the sill, understanding or language to deal with a dancer and their “injury” (Kenny et al., 2018). Research has demonstrated that dancers more commonly access medical attention if it is provided onsite compared to off-site services (Kenny et al., 2018). While time-loss definitions do provide a measure of pain related disability, they may not capture the true impact of the problem within this population, as many dancers continue to dance whilst experiencing pain (Anderson & Hanrahan, 2008; Kenny et al., 2018; Mainwaring, Kerr, & Krasnow, 1993). This may be cultural, as dance populations often persevere regardless of the presence of pain, with phrases like ‘the show must go on”, ubiquitous within performance populations (Anderson & Hanrahan, 2008). As a result of the limitations of using time away from dance to define injury, some researchers have instead quantified the time dancers spend engaged in modified dance activities in order to represent a period "injury" (Bowerman, Whatman, Harris, Bradshaw, & Karin, 2014; Byhring & Bo, 2002; Campoy et al.; Kenny et al., 2018; Negus et al., 2005). Indeed the Self Estimated Functional Impairments due to Pain (SEFIP) scale has been developed to recognise the impact that pain has on function within the context of dance classes and rehearsals (Boeding et al., 2019; Jacobs et al., 2016; Ramel, Moritz, & Gun-Britt, 1999). No studies could be identified which examined pain in dancers sustained outside of dance practice, or the broader impact of pain on activities of daily living outside of dance.

In light of the above outlined limitations of "injury" models in dance, this thesis will adopt more comprehensive measures of pain and related disability. Three separate classifications for musculoskeletal pain will be utilised: 1) Acute traumatic event which will refer to dancer reported incidents such as ankle sprains, muscle tears and fractures, 2) Pain will be considered via subjective reporting of musculoskeletal pain (location and intensity) in the event where there is no acute inciting incident and the dancer is able to continue to dance and participate in normal activities of daily living, and 3) Pain related disability will be considered when a dancer subjectively reports pain that either requires a time period of modified participation or complete cessation of dance training and performance and that impacts the dancer's normal activities of daily living outside of dance. Both pain and pain related disability can include "overuse" related presentations. Further, it is likely that acute traumatic events may lead to disabling pain. All dancers at professional and pre-professional levels have reported experienced disabling pain within their career (Fuller, Moyle, & Minett, 2020; Hincapie, Morton, & Cassidy, 2008; Jacobs, Hincapie, & Cassidy, 2012; Kenny et al., 2018; Volkova & Kenny, 2020). Throughout a dancer's pre-professional training is when pain and it's related disability can be most problematic and the impact of pain on dancers can be substantial (Hamilton et al., 1997). Pain related disability can result in lost training time and is believed to be one of the most common reasons pre-professional dancers cease dance training (Hamilton et al., 1997). For example, within a group of pre-professional dancers (n=40 female, mean (SD) age 14.9 (1) years) at a national level ballet school in America, 50% of students who dropped out in their first year of pre-professional training (n=8) had experienced pain related disability within that year (Hamilton et al., 1997). These dancers had missed over 4 months (109 days) of normal participation in dance classes due to pain related disability (Hamilton et al., 1997). Pain related disability was also cited as a reason for dancers to drop out in their second and third year of their pre-professional training, with less than half of the dancers who commenced this program completing their training and gaining a position in a professional ballet company (Hamilton et al., 1997). Further, pain and pain related disability may impact mental health in dancers. Regardless of anatomical location of pain related disability and dance style, 20% of professional, student and amateur dancers (n=154, 125 female, aged 13-75 years) who sought treatment for musculoskeletal pain and pain related disability demonstrated high levels of psychological distress, measured using the Brief Symptom Inventory (Air, 2013). Dancers demonstrated little change to their distress following treatment for their pain (Air, 2013). Additionally, in a sample of professional and retired Irish dancers (n=178, 111 female, age range of majority 25-34 years) both general and performance anxiety were recognised as psychological problems following pain related disability (Cahalan & O'Sullivan, 2013).

There is general consensus that the lower limb is the most commonly affected area for musculoskeletal pain in dancers (Allen, Nevill, Brooks, Koutedakis, & Wyon, 2012; Ekegren et al., 2014; Gamboa, Roberts, Maring, & Fergus, 2008; Leanderson et al., 2011; Mattiussi et al., 2021; P. J. Smith et al., 2015; T. O. Smith et al., 2016). The majority of pain presentations (54%-85%) are cited as being "overuse" in nature, suggesting that it is the result of repetitive loading (Ekegren et al., 2014; Gamboa et al., 2008; Leanderson et al., 2011). Acute traumatic injuries, which are related to a specific event are less common (Ekegren et al., 2014; Gamboa et al., 2008; Leanderson et al., 2011). A 2016 systematic review and meta-analyses including studies in professional, pre-professional and recreational ballet dancers demonstrated that amongst all dancers, foot and ankle pain was most common with a pooled period prevalence of 25% and 21% respectively (T. O. Smith et al., 2016). The period of time that data was collected over varied between studies (T.O. Smith et al, 2016). When considering pre-professional dancers only the foot and knee were most commonly affected (pooled period prevalence of 29% and 17% respectively) (T. O. Smith et al., 2016). While the meta-analyses did not account for "injury" definition, these results are consistent with more recent publications in pre-professional dancers (Fuller et al., 2020; L. Lee et al., 2017). Amongst pre-professional ballet and contemporary dancers in New Zealand (n=66, 40 female, aged 16-20 years) over the course of a year, 125 "injuries" were reported (L. Lee et al., 2017). "Injury" was defined as *"any physical complaint sustained by a dancer resulting from performance, rehearsal or class and resulting in a dancer injury report or triage, irrespective of the need for medical attention or time loss from dance activities"* (L. Lee et al., 2017). Sixty eight percent of "injuries" affected the lower limb with the foot and ankle being most commonly affected, followed by the knee and then the hip (L. Lee et al., 2017). Similarly, in a smaller cohort Australian pre-professional ballet and contemporary dance students (n=17, 16 female, aged 19-25 years) over the full 3-year duration of their dance, course 119 "injuries" were reported (Fuller et al., 2020). "Injury" was defined as *"any musculoskeletal complaint requiring medical attention"*, where medical attention was provided by an onsite physiotherapist in a triaging and initial advice capacity (Fuller et al., 2020). The most common locations were the ankle (18%), knee (17%) and hip (13%) (Fuller et al., 2020). Of these, only 7 "injuries" were considered traumatic and the rest were considered "overuse" (Fuller et al., 2020). This was substantially lower than that reported in professional ballet dancers over a 5-year period (n=123 professional dancers, 66 female, age range not reported), where 40% of time-loss injuries (n=543) were considered traumatic and 50% were considered overuse (Mattiussi et al., 2021). Considered together, these findings suggest that "overuse" type pain presentations may be more common in pre-professional dancers than professional dancers. However this observation should be considered with caution as only one of these reports clearly defined the classification of "overuse" as *"any medical incident that did not have a sudden onset from a discrete event"* (Mattiussi et al., 2021). Thus, while the available literature suggests that "overuse" type injuries are most common in professional ballet dancers, for pre-professionals it is not quite clear. Low back pain is also common, with reports of a lifetime prevalence of 74%, a point prevalence of 24% and a 12 month prevalence 64% for pre-professional and professional, male and female ballet and contemporary dancers (Swain, Bradshaw, Whyte, & Ekegren, 2017). In pre-professional contemporary dancers (n=134, 90 female, mean (SD) age 19.4 (1.5) years) it has been reported as the second most commonly affected area, with an annual prevalence of 17% (van Winden et al., 2019). However, dependent on how "injury" is defined, prevalence can vary substantially. The seasonal prevalence of musculoskeletal "injury" in a sample of pre-professional Canadian ballet (n=85, 77 female, aged 11-19 years) and contemporary dancers (n=60, 58 female, aged 17-30 years) was reported to range from 9.4% to 82.4%, dependent upon "injury" definition (Kenny et al., 2018). Thus, understanding the true prevalence of musculoskeletal pain in dance is challenging due to variations in pain and injury definition (Kenny et al., 2018).

2.2 Movement quantity and quality as risk factors within a biopsychosocial model of pain

There is growing research supporting the influence of psychological, lifestyle and physical factors as contributing factors towards the development of musculoskeletal pain as well as the dancer's pain experience (Caine et al., 2016; Gallo, Cormack, Gabbett, &

Lorenzen, 2016; Gastin, Meyer, & Robinson, 2013; Gatchel, Peng, Peters, Fuchs, & Turk, 2007). A systematic review has recognised a lack of consensus surrounding the risk factors for the development of pain related disability in dancers, and highlighted the importance of future, high quality, prospective studies to explore the multifactorial nature of pain related disability (Kenny et al., 2016). While it is important that pain and disability is viewed from a broad biopsychosocial perspective, given the physical nature of a dancer's work, and the long-held belief that this is related to the often high rates of pain and disability, specific attention on the relationship between physical factors and pain related disability is required. Within this thesis, the physical factors of interest will be considered under the broad terms of movement quantity, which encompasses the amount of movement a dancer performs within their day, and movement quality, which encompasses the biomechanical demands of the movements.

2.3 Overall movement quantity and pain / pain related disability in dance

There is consensus in the literature that pre-professional and professional dancers undertake persistent high training loads. Pre-professional dancers are reported to partake in 16-30 hours of dance-specific training per week (Ekegren et al., 2014; Gamboa et al., 2008; Volkova & Kenny, 2020). Most of this time is spent in dance classes (77%) or rehearsals (21%) in order to optimally dance in performances that consume a relatively small proportion of time (1.4%) (Ekegren et al., 2014). Professional dancers partake in up to 30-40 hours of class, rehearsal and performance in a typical week (Byhring & Bo, 2002). Data collected on an English ballet company over a 5-year period demonstrated that 27% of this time is spent in class, 50% in rehearsals and 22% in performances (Mattiussi et al., 2021). Historically, high physical training loads have been believed to be associated with the development of pain and disability, however more recently this notion has been challenged, and a general view prevails that pain related disability may be more related with changes in physical training load (Gabbett, 2016, 2020a, 2020b; Gabbett et al., 2016; Gabbett et al., 2014). In dance, this is supported by findings in a recent systematic review and meta-analysis (7 studies included in meta-analysis) (Fuller et al., 2019). The meta-analysis revealed an increase in musculoskeletal pain presentations in the second (rate ratio 1.52 95%CI:1.11, 2.08)) and third months (rate ratio 1.26, 95%CI:1.07, 1.48) after returning to dance training at the start of the year following a break (Fuller et al., 2019). The authors hypothesised that this pattern was likely due to the changes in training loads seen at these times, as well as a potential latent response from when dancers transitioned into full-time training hours at the beginning of the year (Fuller et al., 2019). Additionally, beyond the meta-analysis, systematic analysis of all 17 research papers included in that review suggested that pre-professional dancers generally experienced more pain related disability after returning to dance at the start of the year following a break, and when transitioning from rehearsal periods to performance seasons (Fuller et al., 2019). However these results were inconsistent and some evidence suggested that the increases in pain related disability occurred in later months of the year. Importantly, while this research provides a scope of when dancers may experience pain related disability based on schedules, none of the studies included in this systematic review captured the dancers' movement quantity.

Within the review of the literature, prior to the commencement of this thesis, no publications formally evaluating the relationship of dancers' pain and movement quantity were identified. However, with growing interest in this area, over the last 4 years, 7 studies have explored the relationship between dancers' training load and pain / pain related disability (Boeding et al., 2019; Cahalan et al., 2019; Cahalan, Kearney, et al., 2018; Jeffries et al., 2020; L. Lee et al., 2017; Shaw et al., 2021; Volkova & Kenny, 2020). These studies are summarised in Table 2.1, with particular focus on how movement quantity was measured and how pain/ pain related disability/ "injury" was defined and discussed below.

Table 2.1
Summary of identified publications exploring the relationship between dancers' movement quantity and pain / pain-related disability

Study	Study Design	Dancers	Measure of movement quantity	Definition of pain / pain related disability / injury	Results
(Boeding et al., 2019)	Longitudinal, across 7 training weeks	Professional contemporary dancers n=21 (10 female) mean(SD) age 28 (2) in the Netherlands	"Session RPE"	Self Estimated Functional Inability due to Pain Questionnaire (SEFIP) indicating pain related disability of "overuse injury"	No association between dancers' "session RPE" and SEFIP score (beta coefficient: 0.000145, 95%CI: -0.00043, 0.00333, p=0.127)
(Cahalan, Kearney, et al., 2018)	Longitudinal, across 1 training year	Pre-professional contemporary dancers n=29 (28 female) mean (SD) age 21 (3.1) years and Irish dancers n=21 (20 female) mean (SD) age 21.5 (1.7) years and in Ireland	Self-reported weekly training hours	Any pain or injury that impacted upon the dancers' ability to dance	Contemporary dancers who reported a time loss injury participated in more training hours the week prior to the injury (mean (SD) 18.9 (7.5) hours than over the 4 weeks prior to the injury (mean (SD) 15.2 (7.5) hours) (z= -2.02, r= -0.34, p=0.04). No difference demonstrated for Irish dancers.
(Cahalan et al., 2019)	Longitudinal, across 1 training year	Adolescent Irish dancers n=37 (35 female), aged 13-17 years In Ireland	Self-reported weekly training hours	Any pain or injury that impact the dancers' ability to dance	No relationship between total number of injuries and average hours of dancer per week (risk ratio= 0.91, 95% CI: 0.82,1.02, p=0.11). Significant relationship between average number of hours danced per week and total number of weeks injured (95% CI:0.69,0.92, p=0.001)

Study	Study Design	Dancers	Measure of movement quantity	Definition of pain / pain related disability / injury	Results
(Jeffries et al., 2020)	Longitudinal, across 1 training year	Professional contemporary dancers n=16 (9 females), aged 18-32 in Australia	"Session RPE" (session duration x RPE) Categorised as low, medium and high	Medical attention and time loss definition	No relationship between "session RPE" and injury.
(L. Lee et al., 2017)	Longitudinal, across 1 training year	Pre-professional ballet and contemporary dance students n=66 (40 female) aged 16-20 years in New Zealand	Schedule: hours of dance exposure per month and number of dance exposures per month	Any physical complaint sustained by a dancer resulting from performance, rehearsal or class and resulting in a dancer injury report or triage, irrespective of the need for medical attention or time loss from dance activities	No association between total hours of dance exposure an injury (p=0.964). An association between total number of dance exposures per month and total number of injuries reported across the cohort per month was evident (p=0.016).
(Shaw et al., 2021)	Longitudinal, across 5 training years	Professional ballet dancers n=118 (number of females varied over 5 years) age not reported	Weekly dance exposure measured using dancers' schedules	Recorded by in house medical staff. Defined using both medical attention and time-loss definitions. Categorised as "overuse" or "traumatic"	Week to week increases in dance exposure associated with the rate of overuse, time loss injury (Hazard ratio 1.27, 95%CI 1.06-1.53, p=0.011).
(Volkova & Kenny, 2020)	Longitudinal, across 3 training years	Elite level student ballet dancers n=172 (152 female), aged 10-21 years in Canada	Self-reported weekly training hours	3 definitions: Any physical complaints Physical complaints resulting in time loss Physical complaints requiring medical attention	Weekly reported injury across 3 training years mirrored the fluctuations in weekly training volume

Three of the published studies measured movement quantity using dancers' self-reported training hours per week. One study of full-time elite level student ballet dancers in Canada (n=172, 152 female, aged 10-21 years), found weekly reported "injury" across 3 training years mirrored the fluctuations in weekly training volume (Volkova & Kenny, 2020). "Injury" was defined using 3 definitions; any physical complaints, physical complaints resulting in time loss and physical complaints requiring medical attention (Volkova & Kenny, 2020). A study surveying pre-professional contemporary dancers (n=29, 28 female, mean (SD) age 21 (3.1) years) and Irish dancers (n=21, 20 female, mean (SD) age 21.5 (1.7) years) demonstrated that contemporary dancers who reported an "injury" participated in more training hours the week prior to the "injury" (mean (SD) 18.9 (7.5) hours than over the 4 weeks prior to the "injury" (mean (SD) 15.2 (7.5) hours) (z= -2.02, r= -0.34, p=0.04). injury was defined as "any pain or injury that impacted the dancers' ability to dance" (Cahalan, Kearney, et al., 2018). This relationship did not exist in the Irish dancers. Interestingly however, another study of 37 adolescent Irish dancers (33 female, aged 13 to 17 years) followed over one year and employing the same "injury" definition, also found no relationship between total number of "injuries" and average hours of dance per week (risk ratio= 0.91, 95%CI: 0.82, 1.02, p=0.11) (Cahalan et al., 2019). However a significant relationship existed for the average number of hours danced per week and total number of weeks injured, where for every additional hour danced the weeks injured decreased by a factor of 0.8 (95%CI: 0.69,0.92, p=0.001), suggesting that higher training volume may be protective in relation to training time loss / burden of musculoskeletal pain (Cahalan et al., 2019). In both these studies movement quantity was self-reported by the dancers, thus the measure of movement quantity was potentially prone to bias.

Two of the studies utilised the dancers' schedules to determine dance exposure as a measure of movement quantity. In both these studies a single dance exposure was considered a single dance class / rehearsal / performance. In a sample of pre-professional ballet and contemporary dance students from New Zealand (n=66, 40 female, aged 16-20 years), over the course of a year, dance exposures were recorded and dancers reported any "injuries" every 3 weeks (L. Lee et al., 2017). "Injury" was defined as *"any physical complaint sustained by a dancer resulting from performance, rehearsal or class, and resulting in a dancer injury report or triage, irrespective of the need for medical attention or time loss from dance activities"* (L. Lee et al., 2017). While there was no association between total hours of dance exposure and injury (p=0.964), an association between total number of dance exposures per month and total number of injuries reported across the cohort per month was evident (p=0.016) (L. Lee et al., 2017). In a 5-year prospective study, dancers (n=118, number of females varied over 5-year period, age not reported) in a large professional ballet company, “injury” data was recorded by in-house medical staff, and defined using both medical attention and time loss definitions (Shaw et al., 2021). Additionally “injuries” were categorised as “overuse” and “traumatic”. Week to week increases in dance exposure was associated with the rate of overuse, time loss injury (Hazard ratio: 1.27, 95% CI: 1.06-1.53, p=0.011), however no associations existed for traumatic injuries (Shaw et al., 2021). Additionally, no associations existed for the relationship between injury and both 7-day and 28-day accumulated dance exposure. Combined, these results suggest that “injury” is associated with the way a dancer progresses in their workload, as opposed to accumulated high workloads (Shaw et al., 2021). While a relationship between training load and pain related disability exists, loading that occurs within each of these dance exposures is important. There is great potential for variations in the nature of each dance exposure with respect to volume, intensity, technical and choreographic demand (Liederbach et al., 2006). Therefore, measuring overall movement quantity by time or number of exposures does not provide insight on the quantity of specific movements, nor on the quality of the movements, that the dancers may do within their training.

The other 2 studies which have explored the relationship between dancers’ training load and pain / pain related disability used a measure of movement load created by a product of the duration of a dance activity session and the dancers’ perceived activity intensity, called session rate of perceived exertion (“session RPE”) (Boeding et al., 2019; Jeffries et al., 2016; Jeffries et al., 2020). In a study of Australian professional contemporary dancers (n=16, 9 females, aged 18-32) session durations and RPE were collected for each dancers’ ballet class, contemporary class, rehearsal, and performance over a 1-year period (Jeffries et al., 2020). The relationship between movement quantity and pain related disability was assessed by looking at the incidence of “injury” at different categories of “session RPE” (low, medium, and high). “Injury” was defined using a medical attention and time loss definition and there was no consistent relationship demonstrated between “session RPE” and “injury” (Jeffries et al., 2020). Similarly in a study of professional contemporary dancers in the Netherlands over a 7-week period (n=21, 10 female, mean(SD) age 28 (2)), a linear mixed model demonstrated no association between dancers’ “session RPE” and pain related disability (beta coefficient: 0.000145, 95%CI: -0.00043, 0.00333, p=0.127) (Boeding et al., 2019). Pain related disability was measured using the SEFIP, and all dancers experienced symptoms at some point over the 7-week period. Interestingly, when comparing dancers with and without musculoskeletal symptoms at a single time point, those with no musculoskeletal pain participated in lower training loads compared to those who had musculoskeletal pain and continued dancing (Boeding et al., 2019). However, RPE is subjective and therefore tainted by a dancer's perception, as such "session RPE" is a combination of movement quantity and perceptions of mental and physical loading (Jeffries et al., 2016). Thus, it is possible that dancers perceived greater effort when dancing with musculoskeletal pain, as opposed to actually participating in greater training volumes. Further, while "session RPE" includes the time that a dancer has spent training in class, again it does not directly account for how much a dancer moves in class, the specific movement tasks that dancers perform, and the quality of movement during these tasks. To better understand the relationship between specific movement parameters with pain and pain related disability, the addition of objective quantification of movement quantity is needed, including the quantity of specific movements.

In summary, while all of these studies explored the associations of dancers' movement quantity with pain related disability, measures of movement quantity were limited to dancers' self-report and schedules which may be inaccurate and potentially biased. Further, pain related disability was generally viewed from a variety of definitions of injury, where the relationships between movement quantity and pain related disability were based on the number of pain presentations at a given time point, and did not consider fluctuations in an individual dancer's levels of pain or disability.

2.4 Specific movement quantity and pain / pain related disability in dance

Specific movements that dancers perform may be provocative of pain / pain related disability. For instance, repeated jumping and leg lifting activities have been identified as specific movements that may be associated with the development of musculoskeletal pain (Costa, Ferreira, Orsini, Silva, & Felicio, 2016; Mattiussi et al., 2021).

2.4.1 Jumping quantity and pain / pain related disability

Jumping is an integral part of ballet and contemporary dance and is frequently performed (Mattiussi et al., 2021). Within their movement vocabulary, dancers may have a large range of different jumping movements that they perform. These can broadly be classified into bilateral and unilateral jumps, and small, medium, and large jumps. Two studies have attempted to quantify the number jumps dancers perform (Liederbach et al., 2006; Wyon et al., 2011). Based on the analysis of 16 ballet classes, the first study found that professional ballet dancers perform up to 232 jumps in a typical ballet class, over half of which land on a single limb (Liederbach et al., 2006). This was 38% greater than the number of jumps performed in a professional contemporary dance class (145 jumps), however there was no difference between the number of single limb landings (Liederbach et al., 2006). The other study reported that jumping was more frequent during ballet dance performance than contemporary dance performance irrespective of gender (mean (SD) 5 (5) jumps per minute and 2 (2) jumps per minute respectively, $p<0.001$) (Wyon et al., 2011). In both these studies researchers manually counted the number of jumps directly during a ballet class or using video recording. No further research was found which reported the number of jumps that dancers perform within their normal training. This paucity of research is likely the result of the burdensome methods, for example manual counting of movements. Further, even though dancers consider jumping activities as provocative of musculoskeletal pain, and jumping has been linked to up to a quarter of all musculoskeletal pain presentations in professional ballet (Allen et al., 2012; Mattiussi et al., 2021), no researchers have longitudinally or cross-sectionally analysed the amount of jumping that a dancer performs within their training and how it relates to pain and disability.

2.4.2 Leg lifting quantity and pain / pain related disability

As well as jumping, dancers commonly perform leg lifting tasks. These can vary considerably and include slow and controlled movements and fast, explosive movements, performed to the front, side and behind the dancers' body at varying heights. These repetitive, stereotyped movements, often performed towards the end of their physiological joint range of motion are thought to be provocative of hip and low back pain (Biernacki et al., 2020; Biernacki et al., 2018; Bronner, 2012; Bronner & Ojofeitimi, 2011; Charbonnier et al., 2011; Swain et al., 2017; Swain et al., 2018). However, no studies could be identified that have reported on the quantity of leg lifting that dancers perform within their normal training, nor the relationship between the quantity of this movement and pain and disability in dancers.

In summary, while several studies have evaluated the relationship between movement quantity and pain related disability in dancers, the measures used for movement quantity have been limited to subjective reporting and schedules. These are potentially imprecise and prone to bias, and do not capture specific movements that dancers perform within their training. No studies could be identified that explored the relationship between the quantity of specific movements, in particular jumping and leg lifting activities, and pain related disability.

2.5 Movement quality and pain / pain related disability in dance

Within the current body of work, movement quality refers to the specific biomechanical features of movement which could include aspects such as forces, acclerations, range of movement and variability (Fietzer et al., 2012; Gorwa et al., 2014; Peng et al., 2015).The movement quality features of interest for this research are the peak ground reaction force (GRF) during jumping and thigh elevation and lumbar spine sagittal angles during leg lifting tasks. Ground reaction force is an indication of the total load a dancer is exposed to on landing and the smoothness of landing in a jump, and thus provides indication of movement quality in jumping activities (Slater, Campbell, Smith, & Straker, 2015). Greater peak GRF is thought to be linked to pain, especially when coupled with the large volume of jumping that dancers participate in, or if the dancer's tissue does not have the capacity to tolerate the high loads (Cook & Docking, 2015; Dye, 2005; Mattiussi et al., 2021). Thigh elevation and lumbar spine sagittal angle is related to the characteristic coordinated end of physiological range movements that dancers demonstrate during leg lifting tasks, thus provide indications of movement quality during leg lifting tasks. Large movements are purported to indicate stress on the passive structures of the joint (Han, Kim, Harris, & Noble, 2019).

2.5.1 Jumping movement quality and pain / pain related disability

When Jumping and landing, dancers must conform to a specific aesthetic requirement, whereby dancers are required to execute an apparently smooth and effortless landing (Orishimo, Kremenic, Pappas, Hagins, & Liederbach, 2009). From early in their training, dancers are taught to land initially on the plantar surface of their phalanges before "rolling through" the remainder of their foot, eccentrically controlling their landing into a demi plié, to promote the appearance of a quiet and effortless landing (Orishimo et al., 2009). Despite this, jumping in dance has been associated with high peak GRF of 1.4-9.6 times body weight (BW), which vary substantially between jumping demands (Mattiussi et al., 2021; McPherson, Schrader, & Docherty, 2019). A grand jeté (large jump taking off and landing unilaterally) has been reported as having mean peak GRF from 3.5-9.6BW (Gorwa et al., 2019; Kulig, Fietzer, & Popovich Jr, 2011; McPherson et al., 2019). Smaller dance-specific jumps have been reported to result in smaller GRFs, 3.2-3.4 BW during an assemble (medium jump taking off unilaterally and landing bilaterally) and 1.3-1.5 BW during an echappe saute (small jump taking off and landing bilaterally) (Peng et al., 2015). While GRF is the most widely studied biomechanical variable pertaining to jumping movement quality in dancers, potentially due to being related to pain (Mattiussi et al., 2021), only 3 studies have actually attempted to verify this relationship (Fietzer et al., 2012; H.-H. Lee, Lin, Wu, Wu, & Lin, 2012; Peng et al., 2015).

Within the dance literature, several small, laboratory-based, cross-sectional studies have demonstrated significant differences in GRF between dancers with and without knee pain (Fietzer et al., 2012; Peng et al., 2015). Pre-professional dancers with a history of patella tendinopathy (n=6 [3 female]) demonstrated greater mean peak vertical GRFs than those without patella tendinopathy, during the unilateral landing of a grand jete (n=12 [6 female]; mean difference=1.58BW, P<0.001) (Fietzer et al., 2012). Similarly, female pre-professional dancers with patellofemoral pain (n=11) demonstrated greater peak vertical GRF on landing than those without patellofemoral pain (n=14) during the bilateral landing of an echappe saute (1.58 BW and 1.35 BW respectively; p<0.05) (Peng et al., 2015). Notably, the dancers with patellofemoral pain also jumped higher than those without pain. Thus, it is plausible that the observed difference in GRF was secondary to a difference in jump height rather than the presence of pain, however the authors of this paper hypothesized that the dancers with pain were jumping with greater “effort” (Peng et al., 2015). It is also possible that these dancers were landing with a protective motor response. After repeated jumping, as these dancers fatigued, both the patellofemoral pain group and the pain free group reduced their vertical jump height, however there was no difference in peak vertical GRF compared to prior to fatigue. Conversely, pre-professional dancers with a history of ankle sprain in the last year (n=11) demonstrated no significant difference in GRF compared to those without ankle sprain injury (n=11; p=0.128) during a sissonne fermee (medium jump with unilateral landing) (H.-H. Lee et al., 2012). Considered together, these findings suggest that there may be a relationship between GRF and a history of knee pain but not ankle pain. However, these studies come with several methodological limitations. While all 3 studies were conducted using gold-standard GRF measurement systems, laboratory-based measurements have low ecological validity, that is, it is unlikely dancers perform in a truly natural manner in the artificial setting (Lara & Labrador, 2013). Further, in all studies dancers only completed one type of jumping task, which differed across studies, and the repetitions of the task were limited to only a few trials. As described above, dancers jump more frequently than this within their normal training, and usually perform an array of different jumping tasks within a single training session. Thus, the ability to measure a dancer’s GRF within the field would assist in overcoming these limitations. Further, the analyses compared the movement quality of dancers with and without pain, and did not consider within or between person changes in movement with varying pain intensity or degrees of pain related disability. In fact, in both knee pain studies, while dancers had current pain, and reported disability on valid outcome measures, they did not experience pain during the testing procedure, suggesting that they were able to jump pain free at the time of testing. To our knowledge, no studies in dancers have tracked changes in GRF over time or relative to fluctuations in pain and disability.

2.5.2 Leg lift movement quality and pain / pain related disability

To perform leg lifting movements to the required standard, dancers commonly use large multiplanar ranges of motion at the hip and lumbar spine. During leg lifts performed to the front and side of the body (developpe devant and developpe a la seconde), female dancers (n=11, aged 18-38 years) were reported to require 93° and 95° of hip flexion (measured as the thigh segment relative to the pelvis) respectively (Charbonnier et al., 2011). During a back leg lift (arabesque) dancers were shown to use a much smaller 28° of hip extension (Charbonnier et al., 2011). A different study has reported dancers utilising 23° of hip extension combined with 21° of lumbar spine extension, reflecting the nature of the movement, which combines lumbar spine and hip movement (Bronner, 2012; Mira, Marulanda, Pena, Torres, & Orrego, 2019). These studies utilised laboratory-based 3-dimensional optic motion capture systems to measure the kinematics during these movements. While these systems are considered gold standard for motion analysis, they are once again limited to laboratory-based data collection, with the limitations described above. Further, laboratory-based data collection requires a dancer to step away from their normal training environment, therefore are not optimal for serial monitoring. To date, there do not appear to be any published studies on dancers' leg lifts incorporating serial data. Having a system that could be used within the field, in a dancer's normal training may allow serial monitoring which could provide insight on the role of the dancer's movement quality during leg lifting tasks in the development of pain and pain related disability. While there is a popular belief amongst dancers, clinicians, and researchers alike that these large ranges of motion are proposed to be associated with the development of hip and lower back pain, currently there is no empirical research identified to support this notion.

In summary, GRF and hip and lumbar spine joint angles provide insight of movement quality during jumping and leg lifting activities respectively. While GRF has been associated with knee pain, the true relationship between GRF and pain related disability is unclear. Additionally, there is a need to couple movement quality with movement quantity, to reflect the cumulative training volumes of repetitive jumping and GRF loading. Further, no studies were identified that explored the relationship between leg lifting movement quality and pain related disability. Current studies are limited to laboratory-based research which is not ecologically valid and does not allow for serial monitoring of dancers' movement quality within their normal training environment.

2.6 System for objective measurement of quantity and quality of movement in dance

The current paucity of evidence linking movement quantity or quality with pain and disability might relate to the lack of appropriate objective measurement systems. Current research exploring the relationship of movement quantity and quality with pain related disability also only looks at these factors independently, rather than including both factors. When being related to pain and pain related disability, movement quantity is limited to subjective reporting and schedules, which does not capture movement quality. Similarly, laboratory-based research capturing movement quality in a one-off testing protocol, does not capture the amount of these movements that dancers perform within their day. A field-based system, capable of capturing both movement quantity and quality may overcome these limitations. Such a system could utilise data collected from wearable sensors.

Wearable sensors are small microtechnology units that are typically used to capture the physical movement demands in sport. Most units include one microsensor, or combine microsensors which include global positioning systems, tri-axial accelerometers, tri-axial gyroscopes and tri-axial magnetometers (Chambers, Gabbett, Cole, & Beard, 2015). To our knowledge, while accelerometers are starting to be used in dance to capture overall movement quantity, no specific field-based system has been reported and validated that can measure both dance-specific movement quantity and quality during dance classes and rehearsals. The above-mentioned literature underpins the need to undertake field-based investigations, including comprehensive measures of both movement quantity and quality.

2.7 Wearable sensors in dance

In an effort to perform more ecologically valid research, researchers are turning to wearable sensor technology to objectively estimate movement quantity in the field. To date global positioning systems (GPS) and accelerometers have been the most popular tool for recording movement quantity information representing physical workloads in sport and exercise. Analysis approaches include distances travelled (GPS) and vector magnitude algorithms (applied to accelerometer data) that can categorise daily movement into different intensities (Camomilla, Bergamini, Fantozzi, & Vannozzi, 2018; Chambers et al., 2015; Gabbett et al., 2016; Gabbett & Jenkins, 2011; Gabbett et al., 2014). Researchers have used wearable sensors in team sports to describe the intensity and frequency of match-play demands, such as running in Australian Rules Football and tackling in rugby (Gabbett, Jenkins, & Abernethy, 2010; Gabbett, 2013; Gabbett & Jenkins, 2011; Rogalski, Dawson, Heasman, & Gabbett, 2013). The data generated for these devices is used in the prevention of musculoskeletal pain and pain related disability that may come secondary to changes in training loads (Chambers et al., 2015). While global positioning systems are commonly used in sport, they are not useful in dance as dance is typically performed indoors and within a confined space (e.g. a dance studio or theatre stage) (Kjærgaard et al., 2010). More importantly, the physical demands of dance are, likely, more related to the types of movement a dancer performs rather than the distance travelled or the speed at which the dancer travels that distance. Therefore, accelerometers are more commonly used in dance.

Within dance, accelerometers have been used to measure cumulative movement quantity during professional dancers' working days (Kozai et al., 2020). The results of that study revealed that professional dancers spent and average of 50% of their day (mean (SD) 272 (72) mins) engaged in light activity, compared to 174 (56) minutes at moderate intensity and only 28 (23) minutes in vigorous and 6 +/- 9 minutes in very vigorous activity (Kozai et al., 2020). Accelerometry has also been utilised to report the estimated energy expenditure and physical workload of professional contemporary dancers, by using the vector magnitude to provide an indication of the total stress on the body resulting from accelerations, decelerations and change of direction (Jeffries et al., 2016). The profile of accelerometer tri-axial output also tends to reflect the types of movement that the dancers perform during a choreographed routine (Nagy, Brogden, Orr, & Greig, 2021). During jumping movements there appeared to be a higher contribution of the vertical plane (Nagy et al., 2021). However visual analysis of accelerometer data to determine when jumping occurs is time consuming, thus not practical. While the authors of these studies suggest that the high movement quantity demonstrated by dancers may relate to musculoskeletal pain and disability, they did not analyse this. Further, while the intensity and vector magnitude data generated from accelerometers provide an objective indication of overall movement quantity, these methods of measurement do not provide specific counts of dance-specific movements or information on the quality of movement seen during specific tasks.

Other wearable sensors, such as inertial measurement units (IMUs) may be more useful for movement quantification in dance. Whereas an accelerometer is only able to detect linear accelerations, IMUs combine an accelerometer with a gyroscope and magnetometer (Camomilla et al., 2018). Gyroscopes detect angular acceleration and orientation, and magnetometers detect a specific reference direction (Camomilla et al., 2018). This combination provides increased sensitivity to allow for the detection and analysis of movements (Camomilla et al., 2018; Chambers et al., 2015).

2.8 Machine learning applied to inertial measurement units

Inertial measurement units generate huge data sets, of which processing is cumbersome. Currently this is most commonly via set algorithms, for example customised and manufacturer developed algorithms that process accelerometer data to determine times spent at different exercise intensities as a measure of movement quantity, and sensor fusion techniques to measure joint angles as a measure of movement quality (Camomilla et al., 2018; Chambers et al., 2015). However, to capture more specific movement quantity and quality from raw data, researchers are increasingly using customised machine learning methods (Cust et al., 2019).

Machine learning is an overarching term for a branch of artificial intelligence, which has been applied broadly commercially and in research, and is a rapidly advancing field (Bulling, Blanke, & Schiele, 2014; Cust et al., 2019; Demrozi et al., 2020; Lara & Labrador, 2013). Machine learning models and algorithms are trained to learn from data (Bulling et al., 2014). When applied to wearable sensor data, machine learning has provided new insight into the evaluation of a range of athletic movement demands (Cust et al., 2019; Demrozi et al., 2020). Specifically, researchers have trained models using varied techniques to detect and classify specific athletic movement tasks (human activity recognition) to allow for measurement of movement quantity, as well as provide estimates of quality of movement variables associated with these movements (Argent, Drummond, Remus, O'Reilly, & Caulfield, 2019; Cust et al., 2019; Wouda et al., 2018).

2.8.1 Overview of machine learning methods

Several approaches to machine learning exist and these can be broadly classified as supervised and unsupervised machine learning methods (Demrozi et al., 2020). In supervised learning, a model is created based on the known output data and is used to predict future data points that it has not been trained on (Demrozi et al., 2020). These methods are most used for the application of machine learning to wearable sensor data and include support vector machines and various regression models (such as linear regression, logistic regression, and regression trees) (Demrozi et al., 2020). Unsupervised learning involves identifying patterns in the input data without knowledge of the output (Demrozi et al., 2020). The most well-known unsupervised models include k-means clustering, hierarchical clustering and mixture models (Demrozi et al., 2020). Recently, another field of machine learning known as deep learning has grown in popularity, and computational experts are recommending them over traditional machine learning methods for application to wearable sensor data for measurement of movement quantity and quality as it demonstrates superior accuracy with less required human effort (Cust et al., 2019; Demrozi et al., 2020). Deep learning techniques are based on the concept of data representation (Demrozi et al., 2020; Lara & Labrador, 2013; LeCun, Bengio, & Hinton, 2015). In essence, where traditional supervised and unsupervised models are programmed to identify specific features from the data for subsequent identification, deep learning models automatically generate optimal features from raw wearable sensor data without human intervention (Demrozi et al., 2020; Lara & Labrador, 2013; LeCun et al., 2015). As a result, they may identify patterns for subsequent identification that is otherwise unknown (Demrozi et al., 2020; Lara & Labrador, 2013; LeCun et al., 2015). Examples of deep learning techniques include convolutional neural networks, recurrent neural networks and long short term memory networks (Demrozi et al., 2020; LeCun et al., 2015). As machine learning is a rapidly evolving field, there are continuous advances occurring in the area. Brief descriptions, adapted from Demrozi et al (2020), as well as the advantages and disadvantages of the specific machine and deep learning methods that are pertinent to this body of work are presented in Table 2.2. The large range of machine learning approaches available suggest that there may be more appropriate ways of processing sensor data than currently used algorithms for the measurement of quantity and quality of movement.

Table 2.2

Definitions of machine and deep learning methods (Demrozi et al., 2020)

Machine/ deep learning approach	Description
Support Vector Machine	Supervised machine learning algorithm utilised for classification purposes. Based upon finding a hyperplane that divides a dataset into 2 classes. The support vectors are the data points that lie nearest to the hyperplane, thus if removed would alter the position of the hyperplane. If a data point lies further away from the hyperplane we can be more confident of correct classification. This method generally demonstrates a high degree of accuracy however works better on smaller, clean data sets. It can have high processing demands.
Artificial Neural Networks	Artificial neural networks are able to learn any nonlinear function. They consists of 3 layers of neurons; input, hidden and output.The input layer accepts inputs, the hidden layer processes then and the outer layer produces the results. Artificial neural networks are commonly used for image and tabular data, however are not capable of dealing with sequence data.
Long Short Term Memory Networks	Long short term memory networks are a variant of a recurrent neural network, which learns from sequential time-series dat. In a long short term memory network each, in the middle layer (described above in artificial neural networks) each unit is replaced by a cell which has a gated loop and a system ofgates which controls the flow of information, thus have advantages in modelling sequential dependencies in long-term time-series data and are more computationally effective.
Convolutional Neural Networks	Convolutional neural networks rely upon filters which are used to extract relevant features from input data. the filters are automatically learnt without having to be explicitly taught, similar to the human brain. They are most commonly used for classification of image and video data, where they capture the arrangement of pixels and the relationship between them in an image. They are considered to perform with a very high degree of accuracy, however can have high processing demands.

2.9 Machine learning application for measuring movement quantity: Human activity recognition

A systematic review exploring the applications of machine learning for human activity recognition identified 31 studies which utilised wearable sensor data with degrees of accuracy ranging from 52-100%, however generally the accuracy for specific movement was greater than 90% (Cust et al., 2019). Table 2.3 summarises the details of the included studies and others identified in a literature search conducted July 2018, at the commencement of this research. Since the commencement of this research, another 13 studies have been identified which have applied machine learning models to wearable sensor data for human activity recognition in sports. These studies are summarised in Table 2.4. Overall, models have been developed for activity recognition in range of different sports, including team sports, winter sports, water sports and racquet sports (Cust et al., 2019). As a result, models were developed to identify a range of different movements, specific to each sport. These were inclusive of jumps and shots in volleyball, different styles of aerial jumps in ski jumping, strokes in swimming and shots in tennis (Cust et al., 2019). The tables present the degree of accuracy reported within each development manuscript. The degree of accuracy is important as it reflects the system's performance at accurately detecting specific movements, thus accurate objective quantification of movement quantity (Cust et al., 2019). To date, there have been no reported thresholds identified for acceptable degrees of accuracy in human activity recognition. Further, several factors may have influenced the reported accuracy of the systems. These include the number of people whom data was collected from for model development, the number of sensors used and the location of these, the machine learning approach applied, and the validation approach applied. Where available, these are reported for each study in Table 2.3 and Table 2.4 and described further below in section 2.9.1.

Table 2.3
Summary of human activity recognition in sport publications based on a search of literature in July 2018, prior to the commencement of the study

Reference	Sport: Specific movements identified	Number of sensors (sensor locations)	Participants Number	Machine learning approach(es)	Validation approach	Model performance of best performing model (reported as classification accuracy unless alternative provided)
(Adelsberger & Troster, 2013)	Weightlifting: thruster (squat press)	3 IMU (left ankle, left wrist, lower back)	16	SVM	75% / 25% train-test dataset split	93.4%
(Anand, Sharma, Srivastava, Kaligounder, & Prakash, 2017)	Tennis: forehand topspin, forehand slice, backhand topspin, backhand slice, serve Badminton: serve, clear, drop, smash Squash: forehand, backhand, serve	1 IMU-Accelerometer and gyroscope only (wrist)	31 tennis 34 badminton 5 squash	LR, LSTM CNN	None reported	Tennis: 93.8% Badminton: 78.9% Squash: 94.6%
(Brock & Ohgi, 2017)	Ski jumping: error jump, non-error jump	9 IMU (pelvis, bilateral thigh, bilateral shank, bilateral ski, bilateral arm)	4	SVM, DTW	None reported	52-82%
(Brock, Ohgi, & Lee, 2017)	Ski jumping: 9 motion style errors in flight and landing	9 IMU (pelvis, bilateral thigh, bilateral shank, bilateral ski, bilateral arm)	3	CNN, SVM	8-fold cross validation	93%

Reference	Sport: Specific movements identified	Number of sensors (sensor locations)	Participants Number	Machine learning approach(es)	Validation approach	Model performance of best performing model (reported as classification accuracy unless alternative provided)
(Buckley et al., 2017)	Running: form classified as a fatigued or non-fatigued state	3 IMU (lumbar spine, Right shank, left shank)- note evaluated each separately	21	RF, SVM, kNN, NB	Leave-one-out cross validation 10-fold cross validation	Lumbar spine: 75% Right shin 70% Left shin: 67%
(Büthe, Blanke, Capkevics, & Tröster, 2016)	Tennis: forehand topspin, forehand slice, backhand topspin, backhand slice, smash, shot, steps, side steps	3 IMU (Bilateral foot and racquet)	4	Shots- LCS Steps- SVM	Leave-one-out cross validation	Overall 76% Side steps: 96% Shot steps 63%
(Connaghan et al., 2011)	Tennis: serve, forehand, backhand	1 IMU (arm)	8	NB	10-fold cross validation	Combined accelerometer, magnetometer and gyroscope model: 90% Accelerometer only model: 97% Gyroscope only model: 76% Magnetometer only model: 76%
(Groh, Kautz, & Schuldhaus, 2015)	Skateboarding: ollie, nollie, kickflip, heelflip, pop shove it, 360 flip	1 IMU (skateboard)	7	NB, PART, SVM, kNN	Leave-one-out cross validation	: 97.8%

Reference	Sport: Specific movements identified	Number of sensors (sensor locations)	Participants Number	Machine learning approach(es)	Validation approach	Model performance of best performing model (reported as classification accuracy unless alternative provided)
(Groh, Fleckenstein, & Eskofier, 2016)	Snowboarding: 2 trick categories with 3 trick classes each category	1 IMU (snowboard)	4 for part A, 7 for Part B	NB, kNN, SVM	Leave-one-out cross validation	Grind 90.3% Airs 93.3%
(Groh, Fleckenstein, Kautz, & Eskofier, 2017)	Skateboarding: 11 trick types, trick fail, resting period	1 IMU (Skateboard)	11	NB, RF, LSTM, SVM, kNN	Leave-one-out cross validation	79.8%
(Jensen et al., 2015)	Golf: putt phases, putt event, no putt event	1 IMU (Golf Club)	15	AB	NR	68.2%
(Jensen, Blank, Kugler, & Eskofier, 2016)	Swimming: rest period, turn, butterfly, backstroke, breaststroke, freestyle	1 IMU (back of the head)	11	AB, LR, PART, VM	Leave-one-out cross validation	82.4%
(Jensen, Prade, & Eskofier, 2013)	Swimming: butterfly, backstroke, breaststroke, freestyle, turns	1 IMU (back of the head)	12	DT	Leave-one-out cross validation	95%
(Jiao, Wu, Bie, Umek, & Kos, 2018)	Golf: 9 swing types	1 IMU (Golf Club)	4	CNN	10-fold cross validation	95%

Reference	Sport: Specific movements identified	Number of sensors (sensor locations)	Participants Number	Machine learning approach(es)	Validation approach	Model performance of best performing model (reported as classification accuracy unless alternative provided)
(Kautz, 2017)	Volleyball: 9 skills	1 (wrist of dominant hand)	30	SVM, kNN, Gaussian NB, CART, RF, VOTE	Leave 3 subjects out cross validation	60.3%
(Kautz et al., 2017)	Volleyball: 9 skills	1 (wrist of dominant hand)	30	CNN	Leave 2 out cross validation	79.5%
(Kelly, Coughlan, Green, & Caulfield, 2012)	Rugby union: tackle and non-tackle impacts	1 (between shoulder blades)	9	SCM, HCRF, Learning grid approach with model fusion by AB	None reported	Recall: 0.933 Precision: 0.958
(Kobsar, Osis, Hettinga, & Ferber, 2014)	Running: specific motion patterns based on training background and experience level	1 (lower back)	42	Decomposition using Daubechies 5-mother wavelet	Leave-one-out cross validation	Training background: 96.2% Experience level: 96.4%
(Kos & Kramberger, 2017)	Tennis: Forehand, backhand, serve	1 (wrist of racquet arm)	7	Unsupervised discriminative analysis	None reported	Serve: 96.2% Forehand: 93.5% Backhand: 98.6%
(Ó Conaire et al., 2010)	Tennis: serve, forehand, backhand	6 (bilateral wrists, bilateral ankles, chest, lower back)	5	SVM, kNN	Leave-one-out cross validation	Right arm: 98.41% Full body: 93.44%

Reference	Sport: Specific movements identified	Number of sensors (sensor locations)	Participants Number	Machine learning approach(es)	Validation approach	Model performance of best performing model (reported as classification accuracy unless alternative provided)
(O'Reilly et al., 2015)	Gym: Squatting- correct or incorrect technique and specific technique deviations	1 (low back)	22	Back propagation neural network	Leave-one-out cross validation	Binary classification: 80.45% Multilabel classification: 56.55%
(O'Reilly, D. F. Whelan, Ward, Delahunt, & Caulfield, 2017)	Gym: lunge- different levels of lunge performance and identify aberrant techniques	5 (low back, bilateral thigh, bilateral shank)	80	RF	Leave-one-out cross validation	Acceptable and aberrant technique: 90% Specific technique deviations: 70%
(O'Reilly, D. F. Whelan, Ward, Delahunt, & Caulfield, 2017)	Gym: deadlifting- technique deviations	5 (low back, bilateral thigh, bilateral shank)	135	RF	Leave-one-out cross validation	Binary classification Global classifier 73% Personalised classifier 84% Multi class classification Global classifier 54% Personalised classifier 78%
(Pernek, Kurillo, Stiglic, & Bajcsy, 2015)	Weightlifting: 6 dumbbell lifting exercises	5 (Chest, bilateral wrist, bilateral upper arm)	11	SVM	Leave-one-out cross validation 10-fold cross validation 75 / 25% train-test data set split	84.2-93.6%

Reference	Sport: Specific movements identified	Number of sensors (sensor locations)	Participants Number	Machine learning approach(es)	Validation approach	Model performance of best performing model (reported as classification accuracy unless alternative provided)
(Qaisar et al., 2013)	Bowls: Correct and incorrect medium paced bowls	3 (upper arm, elbow joint and wrist of bowling arm)	1	K-means clustering, Markov Model, HMM	None reported	90.2% Wrist sensor data 100% Elbow sensor data 88.24% Upper arm sensor data 82.35%
(Rassem, El-Beltagy, & Saleh, 2017)	Cross country skiing: gears variations	1 (location not reported)	Not reported	Recurrent LSTM, CNN, MLP	None reported	LSTM: 1.6% class error value CNN: 2.4% class error value
(Rindal, Seeberg, Tjønnås, Haugnes, & Sandbakk, 2017)	Cross country skiing: 8 technique sub-classes	2 (chest and lower arm)	10	NN	Validation data set	96.5%
(Salman, Qaisar, & Qamar, 2017)	Cricket: legal or illegal bowls	3 (upper arm, elbow joint and wrist of bowling arm)	14	SVM, kNN, NB, RF, NN	Leave-one-out cross validation	81%
(Schuldhaus et al., 2015)	Soccer: shot pass, event leg, support leg, other soccer events	2 (bilateral shoes)	23	SVM, CART, NB	Leave-one-out cross validation Validation data set (match conditions)	Leg type: 99.9% Other events: 96.7% Pass or shot: 88.6% Match conditions Shot: 86.7% Pass: 81.7%

Reference	Sport: Specific movements identified	Number of sensors (sensor locations)	Participants Number	Machine learning approach(es)	Validation approach	Model performance of best performing model (reported as classification accuracy unless alternative provided)
(Srivastava et al., 2015)	Tennis: Forehand, backhand, serve, sub-shot types (flat, topspin, slice)	1 (wrist of racquet arm)	14	2 level hierarchical classifier	Not reported	99.4%
(Whiteside, Cant, Connolly, & Reid, 2017)	Tennis: serve, forehand (rally, slice, volley), smash, false shot	1 (wrist of racquet arm)	19	SVM, CT, kNN, NN, RF, DA	10-fold cross validation	Condition 1: 97.4% Condition 2: 93.2%

Abbreviations:
IMU: Inertial Measurement Unit, NR: Not reported SVM: Support Vector Machine, LR: Logistic Regression, LSTM: Long Short Term Memory, DTW: Dynamic Time Warping, RF: Random Forrest, kNN: k-Nearest Neighbour, NB: Naïve Bayesian, LCS: Longest Common Subsequence Algorithm, PART: Partial decision tree, AB: Adaptive Boosting, CART: Classification and regression tree, VOTE: Vote Classifier, HCRF: Hidden Conditional Random Field, HMM: Hidden Markov Model, MLP: Multi-Layer Perceptron, NN: Neural Network

Table 2.4
Summary of published research post 2018 on machine learning applied to wearable sensor data for human activity recognition in sport

Reference	Sport: Specific movements identified	Number of sensors (sensor locations)	Participants Number	Machine learning approach(es)	Validation approach	Model performance of best performing model (reported as classification accuracy unless alternative provided)
(Chambers, Gabbett, & Cole, 2019)	Rugby union: scrum events	1 Accelerometer (thoracic)	30		97 files to train algorithm, 310 to validate performance	Match play: 93.6% Training: 87.6%
(Chambers, Gabbett, Gupta, et al., 2019)	Rugby union: 1:1 tackles and ruck events	1 Accelerometer (thoracic)		RF		Rucks: 79.4% and Tackles: 81%
(Cust, Sweeting, Ball, & Robertson, 2021)	Australian Rules Football: kick types: Binary classification Drop Kicks and all other kicks 4 different kick types)	1 IMU (ankle)	20	RF	70 / 30% split	2 kick: 83% 4 kick: 80%
(Hollaus, Stabinger, Mehrle, & Raschner, 2020)	American Football: catches and drops	2 IMU and audio sensor (bilateral wrist)	8	CNN	75 / 25 split	93%

Reference	Sport: Specific movements identified	Number of sensors (sensor locations)	Participants Number	Machine learning approach(es)	Validation approach	Model performance of best performing model (reported as classification accuracy unless alternative provided)
(Jang et al., 2018)	Cross Country Skiing: 8 techniques	Several IMU Sensor combinations: 17 sensors (whole body worn- pelvis, chest, head, bilateral shoulders, bilateral upper arms, bilateral forearms, bilateral hands, bilateral upper leg, bilateral lower leg, bilateral foot). 11 sensors (upper body only) 7 sensors lower body only 5 sensors (pelvis, bilateral hand, bilateral feet) 1 sensor pelvis	4	CNN LSTM	Training and validation set for each person- validation set representative of a competitive environment. 1 skier used to test. 5 sensor model then used with Leave-one-out cross validation	Whole body model: 87% Upper body model: 80% Lower body model: 70% 5 sensor model: 87% Single pelvis sensor model 64% Leave-one-out cross validation- 5 sensor model 79.7%

Reference	Sport: Specific movements identified	Number of sensors (sensor locations)	Participants Number	Machine learning approach(es)	Validation approach	Model performance of best performing model (reported as classification accuracy unless alternative provided)
(Jowitt, Durussel, Brandon, & King, 2020)	Cricket: Deliveries	1 IMU and GPS (thoracic)	35	RF	Model developed on 21 people and validated on 14	Sensitivity: Training: 96.3%, Match: 99.6% Specificity: Training:98.3% Match: 96.9%
(Kuhlman & Min, 2021)	Basketball: 4 different shots	1 accelerometer (wrist)	NR	SVM	5-fold cross validation	86.3%
(McGrath, Neville, Stewart, & Cronin, 2019)	Cricket- bowling and non-bowling events	1 IMU (thoracic)	17	SVM	10-fold cross validation	100%
(Shahar, Ghazali, As'ari, & Swee, 2020)	Hockey: pass, drive, drag flick, dribbling, receiving, tackling	4 IMUs (chest, waist, bilateral wrist)	11	Cubic SVM	90 / 10% split	4 sensor model: 96.7% 3 sensor model: 94.5-95.7% 2 sensor model: 75.3%-94.8% 1 sensor model: 63.8%-89.8% -

Reference	Sport: Specific movements identified	Number of sensors (sensor locations)	Participants Number	Machine learning approach(es)	Validation approach	Model performance of best performing model (reported as classification accuracy unless alternative provided)
(Stoeve, Schuldhaus, Gamp, Zwick, & Eskofier, 2021)	Soccer: shot, pass and transitions	2 IMUs (bilateral foot)	836 players- 181 sessions (38 field/ 143 lab) Sensor malfunctions- data lost for 292 players	CNN	90 / 10% split	F1 score: 0.93
(Taghavi, Davari, Malazi, & Abin, 2019)	Tennis (3 strokes)	1 Accelerometer (wrist)	8	RF, Linear SVM, kNN	3-fold cross validation	84%
(Xia et al., 2020)	Racquet sports: 4 shot types of badminton, 4 shot types of table tennis, walking	1 IMU (wrist of racquet hand)	5	Multilayer hybrid clustering model	3 subjects for training, 2 subjects to test	86.32
(Zhang, Fu, & Shu, 2019)	Ping pong: 8 short types	1 accelerometer (wrist_	12	RF, CNN	70 / 30% split	RF: 97.8% CNN: 87.55%

Abbreviations:
CNN: Convolutional Neural Network, IMU: Inertial Measurement Unit, NR: Not reported SVM: Support Vector Machine, LSTM: Long Short Term Memory, kNN: K Nearest Neighbour, RF: Random Forrest

2.9.1 Factors that can influence accuracy

Research published prior to the commencement of this thesis demonstrated sample sizes recruited for training and validation of the models ranged from 1 to 135 athletes, and almost half of the published studies trained and tested their models using 10 or less athletes (Cust et al., 2019). Generally this was the same in the research that was published throughout this thesis, however one recent publication utilised data from 836 players (Stoeve et al., 2021). Of note, within this study over a quarter of the players had missing data, mainly due to sensor malfunctions (Stoeve et al., 2021). While models generated using small samples may appear to have acceptable levels of accuracy, as they are only trained and tested on a small group of people they have questionable generalisability beyond the study sample. Greater sample sizes allow for more between person variability in performance of sport-specific movements within the training data, thus potentially creating a more generalisable model (Bulling et al., 2014).

Accuracy may also be influenced by the number of wearable sensors used, as well as the location of sensors. Bulling et al (2014) suggested that for improved movement detection a greater number of sensors, capturing movement at different body segments should be used. More recently, Demrozi et al (2020) recognised that in athletic populations wearing several sensors may not be practical as it may affect athlete performance and a minimum number of sensors is preferable. Thus, while some researchers have used multi-sensor models (i.e., where data is collected from multiple sensor locations), others have developed single-sensor models (i.e., where data is collected from a single sensor location), as shown in the tables. One study has compared the accuracy for different single sensor locations during running, demonstrating superior accuracy with a lumbar spine mounted sensor when compared with lower limb sensors (Buckley et al., 2017). The human activity recognition machine learning model developed in this study was used to recognise if an athlete was running in a fatigued or non-fatigued state (Buckley et al., 2017). Sensor location is potentially very task specific (Bulling et al., 2014). To our knowledge, no researchers have formally evaluated the accuracy of a sensor system with different combinations of both number and location of sensors.

Based on the described methods, the majority of publications both prior to the commencement of this thesis and during the thesis considered movement tasks of interest discretely and did not consider the movements proceeding and following these. Only one study appeared to consider transitions, where they identified a list of specific soccer movements and “other” soccer movements (Schuldhaus et al., 2015). However, this development utilised separate machine learning models to identify the different categories of movements, as opposed to a single model that could detect specific events and transitions (Schuldhaus et al., 2015). The inclusion of transitions in a single model potentially requires a machine learning model to have greater flexibility to being able to recognise any movements that are not the movement of interest, as even with the inclusion of transitions there was reduced performance in a real-world setting. Thus, it can be hypothesised that the inclusion of transitions may reduce the degree of accuracy of the model but improve usability in a real-world setting. However, no reports of studies were identified that formally evaluated this.

The wide range of accuracy may also reflect the machine learning approaches applied. While no identified studies compared methodology of traditional machine learning approaches to deep learning, across two separate studies using the same data set, researchers demonstrated superior accuracy (93%) with the use of a deep learning approach to detect skateboarding manoeuvres than the accuracy shown with traditional machine learning approach (52-82%) (Brock & Ohgi, 2017; Brock et al., 2017). Similarly, superior accuracy was demonstrated using deep learning (80%) compared with a traditional machine learning approach for detecting 9 different volleyball skills (60%) (Kautz, 2017; Kautz et al., 2017). These results suggest, that in the context of human activity recognition, deep learning methods may allow for a higher degree of accuracy.

Multiple validation approaches have been described in order to understand the performance of the machine learning trained model (Cust et al., 2019). Half of the studies in Table 2.3 utilised the same validation approach as an estimate of generalised performance of a trained model, which can be described as a form of “leave-one-out cross validation” (Cust et al., 2019). This is where the model is trained on all participants except one, and then tested on the remaining participant. This process is iteratively cycled through each participant until the accuracy of the model on each participant is known. This approach is favoured as it allows the best indication on how the models will perform on people outside of the training population, thus validating the models. Some studies have altered this approach, by leaving every combination of 2 or 3 participants out instead of 1. These approaches may provide the most conservative validation number (Cust et al., 2019). The main downside of these approaches is that they are inefficient, requiring significant computing time, particularly on large samples. Other less popular validation methods include k-fold validation, where 70% of the data from a combination of any of the participants is used to train the model and the model is subsequently tested on the remaining 30%. Variations of these percentages have also been utilised, particularly in more recently published studies (Jowitt et al., 2020; Stoeve et al., 2021). This method is computationally more efficient and will frequently provide better results as the training and testing data sets include data from the same people. However, these are less generalisable and representative of real-world performance, especially when exposed to unique sets of data (Cust et al., 2019). While the majority of publications both prior to and during the course of the PhD have utilised data collected in a controlled setting, e.g. laboratory or simulated settings, for both development and validation of the models, a recent publication describing the validation of machine learning models for soccer activity detection has stressed the importance of validation of models utilising real-world data (i.e. data collected during a soccer game). While this approach potentially provides greater real-world performance, it may not always be practical.

2.9.2 Human activity recognition for measuring movement quantity in dance

As shown in Tables 2.2 and 2.3, human activity recognition models have been developed for recognition of several different movements in a range of different sports, with varying degrees of accuracy. In applying machine learning models to wearable sensor data for the purpose of human activity recognition, there is a high evolution rate of new machine learning techniques and adaptations. More recently established deep learning methods such as convolutional neural networks appear to demonstrate superior accuracy, and the use of these methods have been suggested for future model developments (Camomilla et al., 2018; Cust et al., 2019). While number of sensors and sensor locations may also influence accuracy, no studies were identified that formally evaluated this.

Within this review of the literature, no studies were identified that have developed a model which detects dance-specific movement tasks, such as jumping and leg lifting tasks. Manufacturer developed machine learning models built into manufacturer specific wearable sensors known as the VERT sensor, for measurement of movement quantity via jump detection have been tested, post thesis model development, in volleyball with a high degree of accuracy (Charlton, Kenneally-Dabrowski, Sheppard, & Spratford, 2017). Average accuracy of detection of jumping events, based on comparison of complete jump counts taken from video data during a volleyball game, was 99.7% and accurate rejection of non-jumping events was 87.9% (Charlton et al., 2017). Further, there was excellent specificity and sensitivity, where 96.8% of jumps and 100% of non-jumping movements were correctly identified (MacDonald, Bahr, Baltich, Whittaker, & Meeuwisse, 2017). It was unclear whether these models included movement transitions, such as stepping or running in between jumps, or how these models were developed, and the described validation was performed on an established product as opposed to during model development. However, given the large number of different jumping movements performed by dancers (outlined above), it is unlikely this product could transfer to dance. Additionally, these manufacturer developed models are only capable of detecting jumping tasks and not other activities that dancers perform, such as leg lifts. However, the outcomes of these two volleyball studies validating this sensor, suggest that a unique model built from wearable sensor data and machine learning could feasibly detect dance-specific movements, allowing for a field-based measurement system for specific movement quantity in dance.

2.10 Machine learning application for measuring movement quality

Machine learning models have also been applied to wearable sensor data to estimate movement quality variables during different activities. Specifically, convolutional neural networks and artificial neural networks have been used to estimate GRFs during the cyclical predictable action of running (Alcantara, Day, Hahn, & Grabowski, 2021; Johnson et al., 2019; Wouda et al., 2018). Joint angles have been estimated using machine learning regression models and artificial neural networks in multiple movements (Argent et al., 2019; Wouda et al., 2018). Analysis is either performed to the full wave form of the movement or of a specific feature of interest such as peak joint angle or peak GRF (Argent et al., 2019; Wouda et al., 2018). Accuracy has typically been reported in these studies using root mean square error (RMSE) and correlation coefficients. Root mean square error is determined by the standard deviation of prediction errors. However, it has been recommended that both RMSE and mean absolute error (MAE) should be included in analysis to provide a better indication of model performance (Chai & Draxler, 2014; Willmott & Matsuura, 2005).

2.10.1 Estimation of movement quality: Ground reaction forces

At the inception of this thesis, to our knowledge, no studies had been published applying machine learning models to wearable sensor data to estimate GRF. A more recent review of the literature has revealed a total of 5 recent studies where machine learning methods had been used to estimate GRF during sporting activities, demonstrating the growing interest in this field (Alcantara et al., 2021; Dorschky et al., 2020; Johnson et al., 2019; Johnson et al., 2021; Wouda et al., 2018). All 5 studies estimated the GRF generated during running. Using a convolutional neural network applied to data from a single sacrum mounted sensor a substantial RMSE of 29.7% (estimated 0.70BW) was demonstrated between the predicted and gold standard force platform values (Johnson et al., 2019). Using 5 wearable sensors, the RMSE reduced to 13.9% (Johnson et al., 2021). This is greater than the RMSE of 6% demonstrated using a convolutional neural network applied to data from 7 wearable sensors, for the estimation of GRF during walking and running (Dorschky et al., 2020). However, the latter study, as well as using more sensors, augmented their sample size of 10 people with simulated data, increasing the amount of data for model development. The models developed on the original data, demonstrated a higher RMSE of 14.4% (Dorschky et al., 2020). Whilst the addition of simulated data increases data sets it may not accurately reflect normal human movement thus results should be interpreted with caution.

Using 3 IMUs, mounted on the sacrum and legs, Wouda et al (2018) developed an artificial neural network machine learning model, capable of detecting GRF during running. The model was developed and validated using 8 runners, and used a leave-one-out cross validation (i.e. the model was trained on 7 participants and tested on one, and this was iteratively cycled through) approach the authors demonstrated a degree of accuracy with a RMSE of 0.39BW (range = 0.21–1.25 BW), with a correlation coefficient of 0.96 across the GRF profile, and no significant difference in peak GRF between the estimated and gold standard force plate values (Wouda et al., 2018). Accuracy improved further when the models were developed and validated on the same person (RMSE range 0.11-0.28BW), however this approach is not useful if a model is going to be used on larger samples as it promotes overfitting (Krawczyk, 2016). Overfitting is when a machine learning model is unable to generalise to an unseen data set, as it has been trained on a dataset without sufficient variability (Krawczyk, 2016). Additionally, to apply the models to larger samples for longitudinal research with current technology it is potentially impractical to train models on individuals. Machine learning models applied to data from a single waistband mounted accelerometer to estimate GRF during running, developed using data from 37 cross country runners, have demonstrated an RMSE of 0.15BW (Alcantara et al., 2021). These results support the notion that training a model on a larger sample not only improves generalisability of the model, but when comparing these results to Wouda et al (2018), also allows for a similar model performance to a model developed and validated on the same person.

To our knowledge, machine learning for the estimation of GRFs from wearable sensor data in a sporting context is limited to running. However, machine learning has also been applied to estimate specific joint forces during sport-specific tasks (Stetter, Ringhof, Krafft, Sell, & Stein, 2019). Application of an artificial neural network to data from two IMUs (thigh and shin mounted) developed using data from 13 participants was able to estimate knee joint force during sports-specific cutting and basic jumping tasks with an average RMSE of 19.1% and correlation coefficients ranging from 0.60-0.94 (Stetter et al., 2019). These results suggest the potential for GRF estimation using machine learning during dance-specific jumping tasks.

2.10.2 Estimation of movement quality: Joint angles

Traditionally, joint angles are derived from IMU data using a sensor fusion algorithm as an indirect measure of segment orientation (Teufl, Miezal, Taetz, Frohlich, & Bleser, 2019). However this method requires several sensors (that require precise positioning either side of every joint being measured), which can be costly and increases processing demands (Camomilla et al., 2018). These methods also rely on the magnetometer in inertial measurement units, which can be highly influenced in the magnetic fields in field-based environments (Camomilla et al., 2018; Vitali, McGinnis, & Perkins, 2020). As a result, machine learning is beginning to be applied to estimate joint angles in clinical and running research, where researchers are using the accelerometer data only or accelerometer and gyroscope data for estimation of joint angles (Argent et al., 2019; Dorschky et al., 2020; Mundt et al., 2020; Wouda et al., 2018).

Using data from either thigh- or shin-mounted sensors on healthy young adults, machine learning models to estimate hip and knee angles during simple rehabilitation exercises (such as active knee and hip flexion) performed by healthy young adults were developed (Argent et al., 2019). The average RMSE for knee angles ranged from 5.7 to 6.1° and for hip from 3.6 to 6.1° (Argent et al., 2019). Machine learning has also been applied to the more dynamic, functional tasks of walking and running. A model capable of estimating multiplanar hip, knee and ankle joint angles was developed using data from 5 sensors (bilateral shin, bilateral thigh and pelvis) using data from 30 healthy adults, demonstrating an average RMSE for joint angle (across all joints and planes of motion) prediction of 4.1° (range 0.5-35°) (Mundt et al., 2020). This performance was similar to that of a convolutional neural network developed using data from 7 wearable sensors worn by 10 people to estimate lower limb joint angles, with an average RMSE of around 5° (Dorschky et al., 2020). Of note, the 7 sensors were worn all on one lower limb, thus to estimate angles of both sides would require 14 sensors (Dorschky et al., 2020). Using fewer sensors (3, sacrum and bilateral shin), and just accelerometer data, Wouda et al (2018) estimated knee sagittal plane angles during running with a similar degree of accuracy. When the model was trained and tested on the same participant (n=8), the RMSE ranged from 1.4° to 4.4° (Wouda et al., 2018). However, as previously mentioned, training and testing the model on the same individual provides a model of very limited generalizability. When this model was trained using the previously described leave-one-out cross validation approach, the accuracy of the model substantially reduced with an RMSE range from 4.8° to 19.5° (Wouda et al., 2018). No reports of applications of machine learning to wearable sensor data for joint angle estimation in sports specific tasks were identified.

2.10.3 Estimation of movement quality in dance

While researchers have employed machine learning methods to estimate movement quality in clinical and sporting contexts, there were no reports identified that applied machine learning models to wearable sensor data for the estimation of either GRF or joint angles in dance.

2.11 The application of machine learning systems applied to wearable sensor systems in field-based research

Despite the development of human activity recognition wearable sensor systems for the measurement of movement quantity in several sports (Cust et al., 2019), and the emerging body of literature demonstrating the use of machine learning for the estimation of movement quality variables, research surrounding these systems are limited to development and validation studies. Additionally, the applications of machine learning data to wearable sensor systems appear to capture either movement quantity or movement quality, with no identified system capturing both. To date, no reports were identified in either sport or dance that have utilised these systems in a field-based study exploring the relationship of movement quantity and quality with pain and pain related disability.

2.12 Summary of the literature

– While there is an emerging body of literature focused on the relationship between movement quantity and pain related disability in dancers, measurement of movement quantity is limited to biased and inaccurate measures that do not capture dance-specific movement tasks.

– While there is some evidence for a relationship between peak GRF and dancers' pain, evidence is limited to small, cross-sectional, laboratory-based studies with low ecological validity.
– Results of sports studies applying machine learning methods to wearable sensor data provides direction towards the potential for the development and application of a field-based wearable sensor system to objectively quantify dancers' movement quantity and quality.

2.13 Aims of the thesis

Within this thesis, we aimed to address the identified gaps in the literature via a series of 3 studies. For the first study data collection was performed in a dance studio utilising wearable sensors and video data, the second study was in a laboratory utilising wearable sensors and a gold standard optical motion analysis system, and the third study was field-based in a pre-professional dance institution and utilised wearable sensors and machine learning models. The aims of the thesis were:

1. To develop and validate a field-based system capable of sufficiently accurate estimates of dance-specific movement quantity and the quality (Study 1, 2A and 2B).
    a) In Study 1, the primary aim was to develop a human activity recognition system using wearable sensor data to accurately measure dancers' movement quantity by identifying specific ballet movements (jumping and leg lifting activities). The primary objective was to determine if machine learning can accurately identify key ballet movements during dance training. The secondary objective was to determine the influence of the location and number of sensors on accuracy.
    b) In Study 2, the primary aim was to develop a series of machine learning models to accurately estimate dancers' movement quality during jumping and leg lifting tasks. The quality of movement variables of interest were GRF during jumping, and peak thigh elevation and lumbar spine sagittal angles during leg lifting tasks. This was achieved through two studies (Study 2A and 2B).
    c) The machine learning models developed and validated were then utilised in the final study, where the aim of this third study was:
2. to determine if there was a relationship of dancers' movement quantity and quality with self-reported pain and pain related disability outcomes across a 12-week period (Study 3).

Chapter Three

3

Study 1:

Development of a Human Activity Recognition System for Ballet Tasks

This Chapter presents findings from Study 1, describing the development and validation of deep learning models for the recognition of ballet-specific jumping and leg lifting tasks, allowing for field-based measurement of movement quantity. Findings from this study have been published and are presented verbatim in this chapter. The full reference for the published manuscript is:

> Hendry, D., Chai, K., Campbell, A., Hopper, L., O'Sullivan, P. & Straker, L. (2020) Development of a human activity recognition system for ballet tasks. *Sports Med Open*, *6*, 20

Ethics approval for this study was obtained from Curtin University Human Research Ethics Office (HRE2017-0185) (Appendix A). An information session was utilised to recruit participants (Appendix B) and participants were provided with a participant information and consent form which they completed prior to commencing the study (Appendix C). The convolutional neural network model developed in this chapter was presented as supplementary digital content in the published manuscript and is presented in Appendix D.

3.1 Introduction

The quantification of training volumes in sport has significantly advanced knowledge regarding the development of musculoskeletal pain disorders in athletes (Gabbett, 2016). Due to a high prevalence of lower limb and lower back pain and associated disability in dancers, there is a growing body of literature focussing on physical training volume in this population (Byhring & Bo, 2002; Gamboa et al., 2008; Twitchett, Angioi, Koutedakis, & Wyon, 2010). Assessment of dancer training volumes have been largely derived from subjective, self-reported measures such as schedules and activity diaries (Byhring & Bo, 2002; Twitchett et al., 2010), which are imprecise and are frequently biased (Halson, 2014). Furthermore, these methods are limited to the number of hours of training / performing, and do not account for individual dancer training volume or specific movements. In quantifying training volume, specific movements likely to be provocative of pain should be considered (Kenny et al., 2016); such as jumping and landing, which has been associated with development of foot / ankle, knee and lower back pain (Costa et al., 2016; Fietzer et al., 2012), and lifting the leg to the front, side or behind the body, which has been associated with hip and lower back pain (Winston et al., 2007). Accurate and detailed measurement of a dancer’s training volume is a key requirement in understanding the relationship between training volume and pain disorders. However, no automated and objective system exists which provides the sensitivity to measure the training volume of specific movements performed by individual dancers.

Small, relatively inexpensive, commercially available wearable sensors have been rapidly adopted in mainstream sports for the objective quantification of training volume (Halson, 2014). Sensor units typically incorporate accelerometery technology to evaluate movement magnitudes and provide an estimation of metabolic demands of sporting activities (Halson, 2014). Specific movement tasks may be better detected using inertial measurement units (IMU), which incorporate accelerometers, gyroscopes and magnetometers allowing for the use of multiple sensor outputs to identify specific movement tasks (Wundersitz et al., 2015). Accelerometers measure the rate of change of velocity via linear accelerations and gyroscopes measure orientation and angular velocity(Henriksen et al., 2018). Magnetometers provide directional information, similar to a compass, by measuring magnetic field strength (Henriksen et al., 2018).

Machine learning algorithms, when applied to IMU data, have provided new insight into the evaluation of athletic movement demands through the automatic recognition of sport-specific movements, via human activity recognition (Chambers et al., 2015).

Machine learning algorithms learn from data and can perform better than manually hard coded rules for complex problems. For example, machine learning algorithms have been applied to data from a single wrist-worn IMU in tennis, demonstrating an accuracy of 97.4% when classifying 3 different tennis strikes (Whiteside et al., 2017). Accuracy reduced to 93.2% when 9 different types of tennis strikes were included in the algorithm (Whiteside et al., 2017), suggesting that machine learning performance reduces with greater levels of feature classification. Further, a manufacturer developed algorithm for detecting jumps during volleyball using a sacrum mounted sensor, with an average precision (accurate detection of relevant events) and recall (accurate rejection of irrelevant events) of 99.8% and 87.9% respectively (Charlton et al., 2017), as well as with excellent specificity and sensitivity, correctly identifying 96.8% of the jumping activities and 100% of non-jumping activities, with no false negatives (MacDonald et al., 2017). These results suggest that there is great potential for human activity recognition using IMU's in dance to provide specific automated means of quantifying dance-specific movements.

Recently, more sophisticated machine learning techniques have been developed, such as deep learning for human activity recognition (Cust et al., 2019; LeCun et al., 2015). Deep learning models are able to automatically learn features from raw data, and are often able to achieve better performance than traditional machine learning because their added complexity allows the models to take greater advantage of larger and more complex training datasets(LeCun et al., 2015). A convolutional neural network (CNN) is a deep learning technique commonly used for image classification and object detection and can be applied to any type of ordered data such as wearable sensor data (time series) for human activity recognition (LeCun et al., 2015).

The placement and number of sensors utilised can influence accuracy of human activity recognition (Attal et al., 2015). Within human activity recognition, the inclusion of multiple sensors at specific locations can impact the accuracy of classification, as well as the variety of activities that can be detected (Attal et al., 2015). However, wearing multiple sensors is burdensome for the athlete. As a result, researchers aim to achieve a minimum number of sensors whilst still developing human activitiy recognition models with the highest possible degree of accuracy (Attal et al., 2015).

Ballet is an art form founded by a number of specific movement activities. Repeated jumping and leg lifting tasks are common ballet movements that have been associated with the development of pain disorders (Khan et al., 1995; Liederbach et al., 2006). Within a single ballet class, dancers can perform over 200 jumps, with a large variety of biomechanical demands and over half of which land unilaterally (Liederbach et al., 2006).

Similarly, dancers may lift their leg to the front, side or behind the body and the speed and pathway of the leg movement depends upon the specific activity they are performing (Bronner, 2012; Bronner & Ojofeitimi, 2011). Finally, activities in ballet are rarely performed in isolation, instead they are dictated by their preceding and proceeding movements, which can be termed transitions. Currently it is unclear as to whether transitions have been incorporated into human activity recognition models for sporting activities. However, when applied to ballet, a human activity recognition model needs to recognise specific activities while also accounting for the large, within activity variations and consider transitions.

While there is a growing body of literature supporting the use of machine learning for activity recognition in sports (Chambers et al., 2015; Cust et al., 2019), based on review of the literature, to our knowledge there are no reports of a machine learning approach to assist in quantifying ballet specific movement tasks. Thus, the purpose of this study was to develop a human activity recognition system using wearable sensor data to accurately identify key ballet movements (jumping and lifting the leg), allowing for objective quantification of training volume in ballet. Our primary objective was to determine if machine learning can accurately identify key ballet movements during dance training. The secondary objective was to determine the influence of the location and number of sensors on accuracy.

3.2 Methods

3.2.1 Participants

We recruited 23 female pre-professional dancers (mean (SD) age: 19.6 (1.2) years) from a university dance institution. Dancers were included in the study if they were currently enrolled in one of the full-time vocational dance training programs at the institution, uninjured at the time of data collection and were participating in a minimum of 8 hours of ballet training per week. Only female dancers were recruited for this study as the movement profile of females and males are different in ballet, where many dance movements are gender specific, and there are differences in the biomechanics demonstrated between males and females (Orishimo, Liederbach, Kremenic, Hagins, & Pappas, 2014). Additionally, there is greater female participation at a pre-professional level. Dancers were excluded from the study if they were currently injured or unwell. This study was approved by the university’s human research ethical committee (HRE2017-0185) with reciprocal ethical approval from the dance institution. Informed consent was obtained from all individual participants included in the study.

3.2.2 Data collection and tasks

Data collection took place in groups of 2 to 5 dancers within a standard ballet studio, equipped with a common sprung dance studio floor. Following a self-directed warm up and attachment of sensors, dancers performed a series of discrete movement tasks commonly performed within classical ballet; jumping and leg lifting tasks (see Table 3.1 and Table 3.2), i.e., the tasks were performed in isolation rather than embedded within a choreographed sequence. The jumping and leg lifting tasks were selected to reflect the movement sequences performed within a typical ballet class and were performed in the same order by all dancers. Jumping tasks incorporated small jumps and large jumps, landing bilaterally and unilaterally, on the right and left leg. The leg lifting tasks were performed to the front, side and behind the body, on the right and left leg. To allow for movement variability between the tasks, timing, magnitude and arm movements for the discrete movement tasks were determined by the dancers, reflecting normal practice. These tasks were then performed within specified choreographed sequences and to music, typical of a normal ballet class. The discrete tasks, including the order they were performed in, and examples of choreographed sequences are detailed in Table 3.2. Data collection for each dancer took approximately 45 minutes.

Table 3.1
Levels of classification for movement tasks

<table>
<tr><th colspan="3">Jumping tasks: Levels of classification</th></tr>
<tr><th>Movement (1)</th><th>Jump type (2)</th><th>Laterality (landing leg) (3)</th></tr>
<tr><td rowspan="5">Jump</td><td>Bilateral landing small jump</td><td>Bilateral</td></tr>
<tr><td rowspan="2">Unilateral landing small jump</td><td>Right</td></tr>
<tr><td>Left</td></tr>
<tr><td rowspan="2">Unilateral landing large jump (leap)</td><td>Right</td></tr>
<tr><td>Left</td></tr>
<tr><th colspan="3">Leg lifting task: Levels of classification</th></tr>
<tr><th>Movement (1)</th><th>Direction of leg lift (2)</th><th>Laterality Lifted leg (3)</th></tr>
<tr><td rowspan="6">Leg lift</td><td rowspan="2">Front</td><td>Right</td></tr>
<tr><td>Left</td></tr>
<tr><td rowspan="2">Side</td><td>Right</td></tr>
<tr><td>Left</td></tr>
<tr><td rowspan="2">Back</td><td>Right</td></tr>
<tr><td>Left</td></tr>
<tr><th colspan="3">Other – used only for models when transitions included</th></tr>
</table>

Table 3.2
Order and description of discrete ballet movement tasks and example of choreographed sequences

Ballet Movement	Description
Leg lifting tasks	
Grands battements *(devant, a la seconde, derriere)*	In a controlled, large amplitude tossing or throwing action the dancer flexes at the hip to bring the lower limb with the knee held in extension) to the front of the body 3 times in succession closing into 5th position each time. The dancer then repeats this movement to the side of the body and then behind the body (hip and lumbar spine extension). This is repeated on the other leg.
Developpe *(devant, a la seconde, derriere)*	In a slow, controlled unfolding movement the dancer lifts the leg to the front of the body. This is repeated to the side and the back. This is repeated on the other leg. This is repeated 3 times.
Battement Lente *(devant, a la seconde, derriere)*	In a slow, controlled movement the dancer lifts the leg to the front of the body, maintaining knee extension. This is repeated to the side and the back. This is repeated on the other leg. This is repeated 3 times.
Jumping tasks	
Sauté in first position	The dancer commences in first position of the feet (lower limbs externally rotated and heels placed together) and performs 8 vertical jumps landing bilaterally.
Changement in 5th position	The dancer commences in fifth position of the feet (lower limbs externally rotated and feet crossed) and performs 8 vertical jumps changing the front foot upon landing.
Entrechat Quatre	The dancer commences in fifth position of the feet (lower limbs externally rotated and feet crossed) and performs 4 vertical jumps beating the legs in air before landing bilaterally with the same foot in front. This was performed with the right leg and left leg starting in front
Assemblé	The dancer commences in 5th position and swishes one leg out to the side as they take off, they gather the legs in the air together and land before immediately taking off for the next jump. This is repeated 6 times.
Jeté ordinaire	The dancer commences in 5th position and swishes one leg out to the side as they take off, they then land on the limb that they swished to the side. This is repeated 8 times
Temps levé	A single leg vertical jump and land performed 5 times in succession
Grand Jeté en avant	A big leap. To prepare for the movement the dancer performed a travelling sequence to generate momentum, as they would normally do within a dance class. This was repeated 2 times on each leg
Grand Jeté en tournant	A big leap turning the body in the air. This was repeated 3 times on each leg

Ballet Movement	Description
Choreographed Sequences Example:	
Slow leg lift sequence	**Developpe devant with right leg**, *lower the leg to pass through first position* to **lift into battement lente derriere**. *Lower the leg into 5th position*. **Developpe the left leg a la seconde**. *Carry the leg, still lifted to derriere*. **Hold the leg lift derriere** and *pivot the body slowly 360°*. *Once returned to original position, close in 5th position. Travelling step into a pirouette*.
Jump sequence	*Travelling step to the right*, **jeté ordinare to the right, temps lev**é *Travelling step to the left*, **jeté ordinare to the left, temps lev**é *Travelling step to the right*, **jeté ordinare to the right, temps lev**é *Travelling step to the left*, assemble **3 changements** *changing direction on each on to turn 360°*

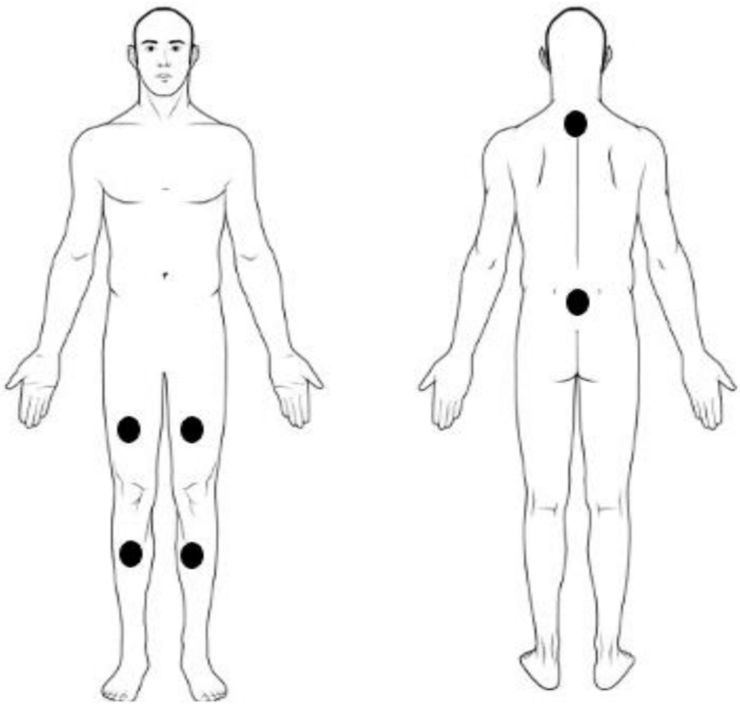
Bold indicates movements for classification, *italics* indicates transition movement

3.2.3 Instrumentation: Sensors and video

Dancers wore 6 ActiGraph Link wearable sensors (ActiGraph Corporation, Pensacola, FL), operating at 100Hz and with the gyrosocope and magnetometer enabled. The Actigraph Link is a small commercially available tri-axial wearable sensor which integrates data from an on-board accelerometer, gyroscope and magnetometer. The ActiGraph sensors were secured to the skin using double sided tape and a single piece of hypoallergenic tape covering at the anatomical locations showed in Figure 3.1.

Sensors were placed on the thoracic spine (used in previous sporting activity recognition research (Gastin, McLean, Breed, & Spittle, 2014; Hulin, Gabbett, Johnston, & Jenkins, 2017; McNamara, Gabbett, Chapman, Naughton, & Farhart, 2015)), sacrum (recommended as this is close to an individual's centre of mass (Attal et al., 2015)) and lower limbs (to capture lower limb movement). On the lower limbs, sensors were placed bilaterally in order to detect the different asymmetrical movements of dance. Both thigh and shin sensors were placed on each lower limb as the shin would likely provide a larger amplitude of acceleration due to the larger axis of rotation (particularly in leg lift tasks), thus providing different information for the human activity recognition model development. Additionally, dancers were simultaneously video recorded using a GoPro Session 5 (GoPro. Inc, USA), capturing 100 frames per second.

Figure 3.1
Wearable sensor locations



Anatomical landmarks for sensor locations:
Thoracic: T2 spinous process
Sacrum: Between the posterior superior iliac spine
Bilateral thigh: Midway between the anterior superior iliac spine and tibial tubercle
Bilateral shin: 10cm distal to the tibial tubercle

3.2.4 Human activity recognition system development

The process of developing the human activity recognition system is described in detail below (Bulling et al., 2014).

3.2.4.1 Data preparation

Following data collection, ActiLife software (Version 6.13.3) was used to output date-time stamped files of each wearable sensor's raw data: including tri-axial accelerometer, gyroscope and magnetometer outputs.

The video data was manually annotated frame by frame by a ballet expert to identify and classify the specific movements at 3 levels (see Table 3.1). The first level of classification determined if the dancer was performing a jump or a leg lifting task. At the second level of classification, jumps were identified based upon size (smaller jumps or large leaps) and whether they landed bilaterally or unilaterally. Smaller jumps included both bilateral and unilateral landings, whereas all large leaps land unilaterally. At the second level of classification, leg lifting tasks were classified by the direction (front, side or back). The third level of classification described laterality of the tasks, i.e., whether the dancer was landing on the right or left leg during unilateral jumping tasks and whether they were lifting their right leg or left leg during leg lifting tasks. Movements that dancers performed that were not these specific movements were left without annotation and considered ‘other’ at all 3 levels of classification.

A customised LabVIEW program (LabVIEW 2017 SP1, National Instruments, Austin, TX, USA) was used to synchronise and merge the 6 sensor files with the video-based specific movement annotations file. Time synchronisation was based on a standardised movement; dancers were instructed to stand still for 5 seconds, then perform a double leg heel raise and then stand still for another 5 seconds at the beginning of data collection. This generated an accelerometry signal which was similar on all sensors, with a period of stillness on either side which could be used for visual synchronisation with the video data. Following synchronisation, unwanted data was removed. Unwanted data were time periods where dancers were not performing the discrete movement tasks or choreographed sequences of movements. This included periods such as breaks, when dancers were being instructed on what movements to perform, as well as short practice sessions performed by the dancers.

3.2.4.2 Segmentation

The data was segmented at a fixed window size of 100 frames to align with the 100Hz sensor and 100 fps video data, resulting in the dataset being split into 1 second segments of data. Additionally, overlapping segments were created in order to capture enough data for detecting events near the window boundaries. An overlap size of 75% was used as it achieved better results compared to other sizes (0%, 25% and 50% were tested).

3.2.4.3 Feature extraction

Initial experimentation was performed, extracting a number of time and frequency domain features commonly used in human activity recognition with wearable sensors (Mannini & Sabatini, 2010; Trost, Zheng, & Wong, 2014; Wundersitz et al., 2015), such as calculating the average and median signal values for various time segments and discrete cosine transforms. These features were used with a number of machine learning approaches including, but not limited to, logistic regression, random forests, support vector machines and shallow neural networks. However, these approaches did not achieve satisfactory results. Convolutional neural networks were therefore used to learn and extract features automatically from the dataset (LeCun et al., 2015).

3.2.4.4 Feature selection

Exhaustive feature selection was applied in order to evaluate all location combinations of sensors for training our models.

3.2.4.5 Classification

A number of CNN architectures were experimented with, using different numbers of layers, filters, filter sizes, activation functions and combinations of convolution and pooling layers. The filter size (layer 1, 25 horizontal, 9 vertical; layer 2, 10 horizontal, 9 vertical) for the convolution layers was selected to allow for filters to learn for each sensor location at a time. i.e., filters to be learnt for the left shin x, y, z along with the accelerometer, gyroscope and magnetometer all at once and then the next sensor location would be learnt. The optimisation algorithm applied to the entire model was the adaptive momentum (Adam) algorithm (Kingma & Ba, 2015).

Two models were developed for each possible sensor combination, 1 without the consideration of transition movements and the second with the consideration of transition movements. Data that was annotated as ‘other’, was considered transition movement.

3.2.5 Determining model performance / statistical testing

The performance of the models were evaluated using a leave-one-out cross validation method (Trost et al., 2014). In the leave-one-out cross-validation, the classification model is trained on data from all of the participants except one, which is ‘‘held out’’ and used as the test data set. The process is repeated until all participants have served as the test data, and the performance evaluation results are averaged (Trost et al., 2014).

To explore the primary aim, determining the performance of the model in detecting the movement tasks, the models were evaluated using all 6 sensors, at each of the 3 levels of classification. The models developed without consideration of transition movements allowed comparisons with existing literature, while the addition of transitions allows for greater ecological validity (Lara & Labrador, 2013). To explore the secondary aim, determining to what extent the number and location of sensors affect performance of the model, the model was evaluated using all other possible sensor combinations (i.e., all possible combinations for 5 sensors, 4 sensors, 3 sensors etc) at each of the 3 levels of classification. This allowed determination of the best combination for each number of sensors. To interpret the performance of the models, confusion matrices were constructed for each participant with every combination of sensors and averaged across the population.

The components of a confusion matrix are demonstrated in Figure 3.2. This was used to calculate the degree of accuracy for each model in classifying the movements at each of the 3 levels of classification for all sensor combinations. Accuracy was calculated by the sum of the true positive and true negative divided by the total (Whiteside et al., 2017).

Figure 3.2

Components of a Confusion Matrix

Actual \ Predicted	+ve	-ve
+ve	True positive (tp)	False negative (fn)
-ve	False positive (fp)	True negative (tn)

$$\textit{Accuracy} = \frac{tp + tn}{total}$$

Definitions of terms:
True positive: Cases where the model correctly identified the activity
False negative: Cases where the model correctly identified when the activity was not performed
False negative: Cases where the model incorrectly identified the activity
True negative: Cases where the model incorrectly identified when the activity was not performed

3.3 Results

3.3.1 All 6 sensors

At the first level of classification, including all 6 sensors, the model without transitions performed with 97.8% accuracy. The degree of accuracy reduced at the second and third levels of classification to 83.0% and 75.1% respectively. When transitions were included the performance of the model reduced to 84.2% accuracy at the first level of classification, 77.1% at the second level and 73.5% at the third level.

3.3.2 Different sensor combinations

Without transitions the model performed with a high degree of accuracy at the first level of classification regardless of the number of sensors the dancer was wearing (see Table 3.3). At the second and third levels of classification there were reductions in performance of the model with reduced sensors regardless of the sensor combination (see Table 3.3).

A similar trend existed when transitions were applied (see Table 3.4).

Table 3.3
Degree of accuracy for different sensor combinations at all 3 levels of classification- without transitions

# sensors *number (number of possible sensor combinations)*	**Level 1** **Accuracy Score** *Mean (Range)*	**Level 1** **Best**	**Level 1** **Worst**	**Level 2** **Accuracy Score** *Mean (Range)*	**Level 2** **Best**	**Level 2** **Worst**	**Level 3** **Accuracy Score** *Mean (Range)*	**Level 3** **Best**	**Level 3** **Worst**
5 (6)	98.2% (98-98.5%)	L shin L thigh R shin R thigh Sacrum	L thigh L shin R thigh Sacrum Thoracic	81.8%% (81.3-81.8%)	L shin L thigh R shin R thigh Sacrum	L shin L thigh R thigh Sacrum Thoracic	74.9% (74.1-76.3%)	L shin L thigh R shin R thigh Sacrum	L shin L thigh R thigh Sacrum Thoracic
4 (15)	98.1% (97.8-98.4%)	L shin L thigh R shin R thigh	L thigh R shin R thigh Sacrum	81.3% (79.3-82.4%)	L shin R shin R thigh Sacrum	L shin L thigh Sacrum Thoracic	73.8% (71.8- 75.1%)	L shin R shin R thigh Sacrum	R shin R thigh Sacrum Thoracic
3 (20)	98% (97.6- 98.2%)	L shin R thigh Sacrum	R shin Sacrum Thoracic	79.5% (73.7-81.7%)	L shin R shin Sacrum	L shin L thigh Thoracic	72.0% (65.2-74.5%)	L shin R thigh Sacrum	L shin L thigh Thoracic
2 (15)	97.7% (97.2-98.1%)	L shin R thigh	Sacrum Thoracic	75.8% (69.7- 80.2%)	L shin R thigh	L shin L thigh	68.0% (61.5-72.5%)	L shin R thigh	L shin Thoracic
1 (6)	97.3% (97-97.7%)	R Thigh	R Shin	67.1% (60.2-76.5%)	Sacrum	Thoracic	56.5% (38.0-65.3%)	Sacrum	Thoracic

Table 3.4

Degree of accuracy for different sensor combinations at all 3 levels of classification- with transitions

# sensors	**Level 1**			**Level 2**			**Level 3**		
number (number of possible sensor combinations)	**Accuracy Score** *Mean (Range)*	**Best**	**Worst**	**Accuracy Score** *Mean (Range)*	**Best**	**Worst**	**Accuracy Score** *Mean (Range)*	**Best**	**Worst**
5 (6)	84% (83.6-84.4%)	L shin L thigh R shin R thigh Thoracic	L thigh L shin R thigh Sacrum Thoracic	76.2% (75.9-76.6%)	L shin L thigh R shin R thigh Thoracic	L shin, L thigh R shin R thigh Sacrum	73.6% (73.2-74%)	L shin L thigh R shin R thigh Sacrum	L shin L thigh R shin R thigh Thoracic
4 (15)	83.4% (82.5-84.0%)	L shin R shin R thigh Sacrum	L shin L thigh Sacrum Thoracic	75.3% (74.5-75.9%)	L shin R shin R thigh Thoracic	L shin L thigh Sacrum Thoracic	73.0% (71.5-74%)	L shin L thigh R shin R thigh	L shin L thigh Sacrum Thoracic
3 (20)	82.9% (82.1-83.6%)	L shin R shin Thoracic	L shin L thigh Sacrum	73.9% (70-75.4%)	L shin R shin Sacrum	L shin L thigh Thoracic	71.6% (67.1-73.3%)	L shin R shin R thigh	L shin L thigh Thoracic
2 (15)	82.1% (81.2-82.9%)	L shin R high	L shin Thoracic	71.2% (67.3- 74.4%)	L shin R thigh	L shin Thoracic	68.5% (64-71.8%)	L shin R thigh	L shin Thoracic
1 (6)	80.6% (78.0-81.6%)	R thigh	Thoracic	64.7% (58.5- 70%)	Sacrum	Thoracic	61.0% (47.4-67%)	Sacrum	Thoracic

3.4 Discussion

Using triaxial accelerometer, magnetometer and gyroscope outputs of 6 wearable sensors, a CNN model was trained to identify dance-specific jumping and leg lifting tasks at 3 different levels of classification. Models based on data without transitions performed superiorly to models which considered transition movements. There was a gradual reduction in model performance with increased levels of classification and performance also reduced with reduced sensor numbers and for different sensor location combinations.

At the first level of classification, determining if the dancer was jumping or lifting their leg, using all 6 sensors, and not including transitions, the model developed in this study performed superiorly to previously developed human activity recognition algorithms in sport (Chambers et al., 2015; Cust et al., 2019; Kautz et al., 2017; Wundersitz et al., 2015), with an average degree of accuracy of 98.2%. Convolutional neural networks have previously been applied to a single wearable sensor's accelerometer output to identify 10 different specific strikes in beach volleyball at a single level of classification with a lower classification accuracy of 83.2% (Kautz et al., 2017). The results of the current study are closer to those of machine learning programs which have been developed for the recognition of bowling tasks in cricket (99% specificity and 98.1% sensitivity) (McNamara et al., 2015), and tackles in rugby (97.6% accuracy) (Hulin et al., 2017). While manufacturer developed algorithms have been developed to detect jumping on other sporting populations with similar accuracy, these have not been validated in dance-specific jumps (Charlton et al., 2017; MacDonald et al., 2017). Further they only detect jumping movements and not activities (Charlton et al., 2017). Therefore, the current study provides a system to detect specific dance movements for training volume monitoring in dance, that is as robust as that being used for movement measurement in elite sport.

As expected, the inclusion of transition movements reduced the accuracy of the model at the first level of classification (mean accuracy 84%). To our knowledge, no previously developed human activity recognition models and algorithms have applied transition movements in the development of their models within sport. The inclusion of transitions is more ecologically valid as movement is rarely performed discretely, rather within the context of the sport or activity they are part of (Lara & Labrador, 2013). While the application of transitions reduced the accuracy of the model, developing a model with transitions will likely promote superior real-world performance of the system (Lara & Labrador, 2013). With this in mind, we contend that future system developments should include transition movements within the model development. As a result, the remainder of this discussion will reflect the results including transitions.

The degree of accuracy reduced with increasingly complex classification levels; from 84.2% at the first level, to 77.1% at the second and 73.6% at the third level. This supports previous findings of diminishing accuracy with increasing complex classifications during tennis (97.4% at level 1, and 93.2% at level 2) (Whiteside et al., 2017). While there are currently no thresholds defined in terms of acceptability in degree of accuracy, a potential error rate of between 15.8% at the first level of classification and 22.9% at the second level, is still superior to self-reported measures which can have errors of up to 36.9% (Phibbs et al., 2017).

The human activity recognition system presented included 3 levels of classification, providing additional critical information that is not reflected in training schedules (Twitchett et al., 2010), nor in manufacturer developed algorithms for jump detection (Charlton et al., 2017; MacDonald et al., 2017). At the second level of classification the jumping tasks were classified based upon jump size and whether the dancer landed bilaterally or unilaterally. This information may be pertinent given that during unilateral landings, the substantial GRFs evident in dancers are absorbed by a single leg (Liederbach et al., 2006), imposing greater risk towards musculoskeletal pain development (H.-H. Lee et al., 2012). The leg lifting tasks were categorised according to leg lift direction. This might help inform musculoskeletal risk, given that repeated leg lifting tasks to the front and side of the body have implications for the development of hip pain, while repeated leg lifting tasks behind the body have implications for the development of back pain (Khan et al., 1995). At the third level of classification laterality was identified with jumps and leg lifts, with an accuracy of 73%. Of note this is the first human activity recognition system developed that includes laterality. Despite the overall decreased accuracy of the human activity recognition with increased classification, this detailed information may provide critical insights to better understanding the relationship between training volumes and musculoskeletal pain in this population.

Our results demonstrate diminished accuracy with decreased number of sensors, particularly at the second and third levels of classification. It is likely that this was due to a greater number of potential activities that were being recognised at these levels, thus reducing the size of the data set for each activity, and also looking at the activities in greater detail. Interestingly, the best sensor combination for 5, 4, 3 and 2 sensors all included the right thigh and left shin sensors. We believe that this is because of the, largely, lower limb dominant and asymmetrical nature of ballet movements, where bilateral sensors located in different locations would provide varying information to a human activity recognition model. Thus in future human activity recognition model developments, sensor location on each lower limb should be considered.

Wearing multiple sensors can be burdensome to the dancer, as well as require greater equipment, data collection, and processing demands (Lara & Labrador, 2013). Additionally, the aesthetics of ballet focus on clean, unimpeded movements and line of the leg and torso, in both training and performance settings (Chang et al., 2016). It is unlikely that an elite dancer or athlete would regularly wear 6 sensors, and within other sports a single upper back worn sensor is more common (Hulin et al., 2017; McNamara et al., 2015). Our study demonstrated a single sensor worn on the upper back having the poorest accuracy. This may be due to the nature of the tasks considered which are lower limb dominant, and dancers maintain an upright posture through the thorax. Our results do however indicate that a single sensor worn on the sacrum would allow for reasonable accuracy in detecting the movement tasks of interest to this study, at the first and second levels of classification (81.5% and 70% respectively). This may be optimal, as a single sensor on the sacrum is easily concealed providing scope for the use of the sensor system without detracting from the traditional aesthetic lines created in classical ballet, nor impeding the dancers' movement.

3.4.1 Strengths and limitations

This system can be used to measure a dancer's training volume with regards to multiple specific movement tasks, providing coaches, medical staff and dancers with information for training volume monitoring and implication for pain development. The accuracy achieved by the models is promising with the strengths being; the dance population the models were developed on, and ecological validity of the data collected. The dancers involved in the study represented a cross section of pre-professional dancers enrolled in a university pre-professional dance program, inclusive of both classical ballet and contemporary dance majors, thus displayed a range of differences in technical abilities. The benefit of this is that the human activity recognition system should be generalisable to a range of pre-professional dancers with varying abilities, however the system may not be accurate in activity recognition for either less experienced dancers, or more experienced, professional dancers. Additionally, the inclusion of transition movements allows for greater real-world application of the human activity recognition system.

This human activity recognition system was limited to the recognition of jumping and leg lifting tasks and developed using only a female population of dancers. Further development of a system to measure training volume in dancers should include a greater variety of movement tasks such as pirouettes, pointe work and travelling phrases of movement. Such development should also include male dancers, considering specific movements that have been associated with the development of pain in male dancers, such as partnering work, lifting and jumping. As technological advances in wearable sensors continue, embedded sensors in dancers' footwear and attire may also promote further opportunity.

While the models in the current study are developed to recognise dance-specific movement tasks, the methodology demonstrated is transferrable and generalisable for human activity recognition of other lower-limb dominant sporting activities, such as kicking in Australian football and soccer, or specific jumping tasks demonstrated during athletics and basketball. Methodologically, one of the limitations of the use of CNNs for the human activity recognition model development is that it is unable to be ascertained which specific sensor outputs have been utilised in recognising the activities, thus we are not able to comment on the role of the accelerometer, magnetometer and gyroscope outputs to inform future developments. However, our results highlight the importance of the inclusion of transition movements in human activity recognition model development and also consideration of activities at multiple levels of classification, allowing for further insight on the specific workloads that athletes are exposed to within training and competition.

3.5 Conclusions

A human activity recognition model developed with transition movements was robust enough to identify jumping and leg lifting ballet tasks in real world exposures. Further, the human activity recognition model could provide some indication of size of the jumps, whether the dancer was landing bilaterally or unilaterally and the direction that the dancer was lifting the leg. While the use of all 6 sensors provided the most accurate identification, fewer sensors still provided a respectable degree of accuracy in detecting the specific tasks. Further, this model of human activity recognition could be applied to other sports to more accurately assess exposures and thus better understand mechanisms of performance and musculoskeletal pain conditions.

Chapter Four

4

Study 2A:

An Exploration of Machine Learning Estimation of Ground Reaction Force from Wearable Sensor Data

This Chapter presents findings from Study 2A, describing the development and validation of machine learning models for the estimation of ground reaction force (GRF) during commonly practiced ballet jumps, allowing for field-based measurement of movement quality. Findings from this study have been published and are presented verbatim in this chapter. The full reference for the published manuscript is:

> Hendry, D., Leadbetter R., Mckee, K., Hopper, L., Wild, C., O'Sullivan, P., Straker, L. & Campbell, A. (2020) An exploration of machine learning estimation of ground reaction force from wearable sensor data. *Sensors*, *20*(3), 740

Ethics approval for this study was obtained from Curtin University Human Research Ethics Office (HRE2017-0185) (Appendix A). A recruitment flier and social media posts were utilised to recruit participants (Appendix E) and participants were provided with a participant information and consent form which they completed prior to commencing the study (Appendix F).

4.1 Introduction

Ground reaction force (GRF) is a commonly measured biomechanical feature during impact-based activities such as landing from a jump (Devita & Skelly, 1992; Harwood, Campbell, Hendry, Ng, & Wild, 2018; Hendry, Campbell, Ng, Harwood, & Wild, 2019; Pappas, Sheikhzadeh, Hagins, & Nordin, 2007; Slater et al., 2015). Peak values of the GRF during jumping typically exceed several times an athlete's body weight (BW) (Devita & Skelly, 1992; Slater et al., 2015). For example, laboratory-based studies have demonstrated that basketballers, volleyball players, and runners exhibit peak GRFs between 2–5 BW (Devita & Skelly, 1992), and gymnasts land a frontsault with up to 15.8 BW (Slater et al., 2015). Ballet dancers are aesthetic athletes who have been reported to perform up to 220 jumps within a single training session, from over half of which they land unilaterally (Liederbach et al., 2006), with peak GRFs commonly exceeding 4 BW (Hendry et al., 2019; Jarvis & Kulig, 2016). High GRF during landings may increase the accumulated internal loads that these athletes experience during training, competition and performance, thus increasing susceptibility to musculoskeletal pain conditions (Kiernan et al., 2018; Pappas et al., 2007). For example, recreational athletes have demonstrated 3.4%–6.5% higher peak vertical GRF on landing when fatigued (Pappas et al., 2007). Similarly, high peak GRFs during impact-based activities have been associated with the development of lower limb musculoskeletal pain conditions (Kiernan et al., 2018). Therefore, GRF is considered an important issue for dancers.

GRF is commonly measured in laboratory studies using force platforms (Devita & Skelly, 1992; Harwood et al., 2018; Hendry et al., 2019; Liederbach, Kremenic, Orishimo, Pappas, & Hagins, 2014). The output from a force platform provides a complete GRF profile, allowing identification of the GRF at any point during the jump. However, force plates are expensive and restricted by their dimensions, and thus are typically unable to assess complicated athletic manoeuvres, such as series of jumping tasks commonly performed in ballet. Importantly, these systems are not ecologically valid (Sinclair et al., 2013), i.e., they are unable to capture a dancer's movement in a normal training environment or across a performance season or training period, where changes in movement due to factors such as fatigue may be common. As a result, there is a need for a field-based system for measuring GRF during jumping tasks.

Recent advancements in wearable technology has opened the possibility of field-based GRF measurement, providing biomechanical insight in sports where laboratory-based measurement is challenging. For example, force insoles have been added to ski boots for analysis of ski jump landings (Bessone, Petrat, & Schwirtz, 2019), and bendable outsoles used for GRF measurement during walking (Park, Kim, Na, Kim, & Kim, 2019). Within a dance population, the addition of an insole or outsole to a ballet shoe is not possible due to the aesthetic and technical requirements of the athletic pursuit. Rather, wearable technology potential in this population lies in small, body-worn, commercially available wearable sensors (Benson, Clermont, Bosnjak, & Ferber, 2018; Johnson et al., 2019; Leporace, Batista, Metsavaht, & Nadal, 2015; Shahabpoor et al., 2018; Tan, Chiasson, Hu, & Shull, 2019; Wouda et al., 2018).

Traditionally, wearable sensor accelerometer data has been used in the field during walking and running activities to estimate force directly using inverse dynamics (Ancillao, Tedesco, Barton, & O'Flynn, 2018; Benson et al., 2018; Shahabpoor et al., 2018; Tan et al., 2019). However, given the noisy signal, this method has variable success (Ancillao et al., 2018). Most current wearable sensors contain multiple hardware chips such as inertial measurement units (IMUs), which combine an accelerometer, magnetometer and gyroscope. Rather than directly entering the derived data into calculations, sports scientists are applying sophisticated machine learning algorithms to indirectly estimate GRF using data from these sensors (Johnson et al., 2019; Leporace et al., 2015; Wouda et al., 2018). Machine learning models have been applied to both multi-sensor and single sensor data in order to estimate GRF during running (Wouda et al., 2018). Using 3 IMUs, mounted on the sacrum and legs, Wouda et al (2018) demonstrated a RMSE of 0.39BW (range= 0.21-1.25 BW), with a correlation coefficient of 0.96 across the GRF profile, and no significant difference in peak GRF between the predicted and gold standard force plate values. While these results are promising, running is characterised by a rhythmical, consistent and predictable movement profile.

Machine learning has also been applied to estimate other biomechanical forces. For example, data from two IMUs for knee joint force estimation during sports-specific tasks, such as cutting and basic jumping tasks (Stetter et al., 2019). This model demonstrated reduced accuracy (average RMSE of 19.1%) compared to that used in running, potentially due to more variable movement patterns (Stetter et al., 2019). Further research is required for development of such models for GRF during complex, sports-specific tasks such as jumping. Additionally, within the unique context of dance, a system requiring a minimum number of sensors is required to conform within the aesthetic requirements.

The purpose of this study was to develop a series of machine learning models capable of predicting peak GRF during bilateral and unilateral dance-specific jumping tasks. A field-based measurement of these biomechanical features would enable exploration of the role of GRF in the development of musculoskeletal pain conditions in people when engaging in lower-limb loading tasks.

4.2 Materials and methods

The Consensus-based Standards for the Selection of Health Measurement Instruments (COSMIN) provided guidelines for the design and reporting of this study [17].

4.2.1 Participants

Thirty female ballet dancers (mean (standard deviation, SD) age: 18.50 (1.68) years, mean (SD) weight (kg): 54.7 (3.3) kg) were recruited from ballet schools across Perth, Western Australia. Dancers were included in the study if they were aged 16 years or older and participating in a minimum of 6 hours of ballet training per week. Only female dancers were recruited for this study as the movement profile of females and males are different in ballet, and there is greater female participation at a pre-professional level. Both recreational and pre-professional dancers were included in the study to allow for greater diversity of skill level, and thus variability of movement for model development. Dancers were excluded from the study if they were currently injured or unwell. This study was approved by the university's human research ethics committee (HRE2017-0185). Informed consent was obtained from all participants included in the study.

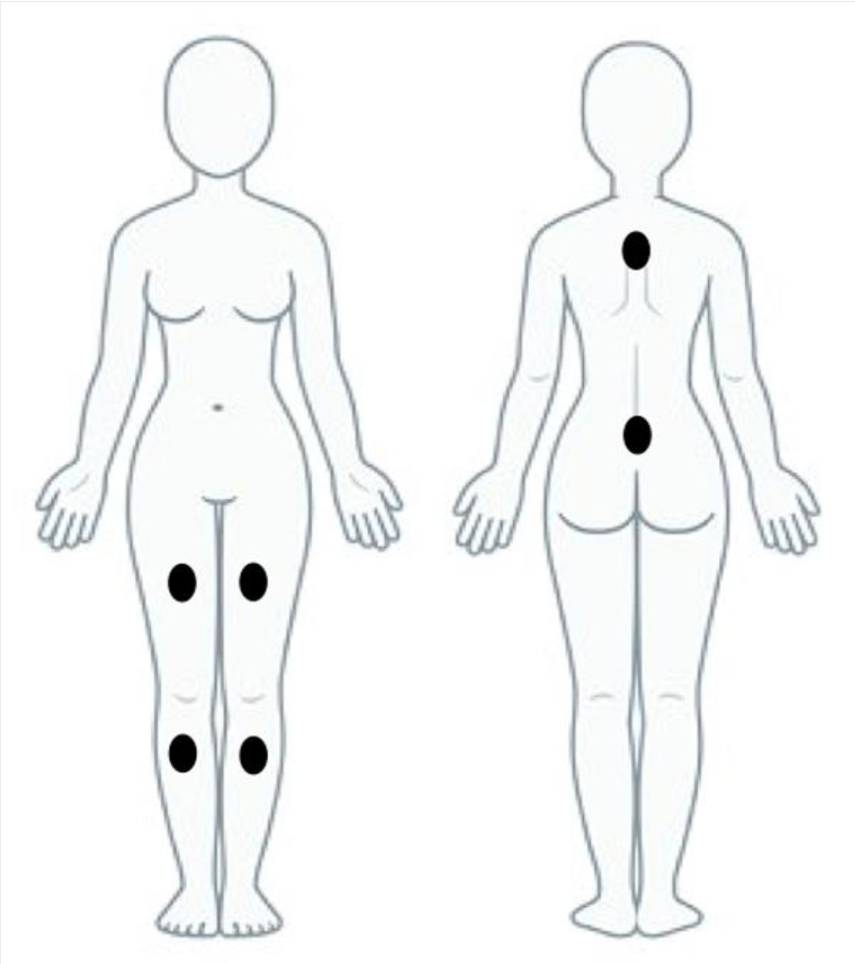
4.2.2 Data collection

Dancers attended a single data collection session at the university's motion analysis laboratory. Following completion of a short questionnaire detailing their current dance participation and years of dance experience, body mass, height and limb measurements (lower limb length, knee width, ankle width) were recorded using calibrated scales (Tanita Corporation of America, Arlington Heights, Illinois, USA), a stadiometer (Mentone, Victoria, Australia) and a tape measure.

All jumps were performed on a single force plate (Advanced Mechanical Technology, Inc., Water-town, Massachusetts, USA) operating at 2000 Hz. The force platform was covered with a thin, soft mat attached to the platform to better simulate a dance floor.

Dancers were fitted with 6 ActiGraph Link wearable sensors (ActiGraph Corporation, Pensacola, FL), operating at 100 Hz and with the gyroscope and magnetometer enabled. The ActiGraph Link is a small commercially available tri-axial wearable IMU. The sampling frequency of 100 Hz was selected as this was the maximum sampling frequency available on this device. The ActiGraph sensors were secured to the skin using double-sided tape (3M 1522 Medical Tape, double sided, transparent, 3M, MN, USA), where the double-sided tape was placed between the sensor and the skin. This was then further secured using a single piece of hypoallergenic tape (Rocktape, Australia), which covered the sensor so that it did not dislodge during jumps. The double-sided tape is non-elastic and commonly used within biomechanical research, the hypoallergenic tape is elastic so as not to restrict the dancers' movements. Sensors were placed on the thoracic spine, sacrum (recommended as this is close to an individual's centre of mass) and bilateral shin and thigh (to capture lower limb movement) (See Figure 4.1).

Figure 4.1
Anatomical locations of inertial measurement units (IMUs)



IMU locations:
Thoracic: T2 Spinous Process
Sacrum: Between the posterior superior iliac spine
Bilateral Thigh: Midway between the anterior superior iliac spine and tibial tubercle
Bilateral Shin: 10cm distal to the tibial tubercle

Lower limb sensors were placed anteriorly on the thigh to avoid obstruction of movement. All sensor locations also allowed for easy attachment to the dancer's skin, reducing the potential impact of movement artefact from clothing interfering with the sensors. The sacrum sensor can be concealed easily, thus conforming with the aesthetic requirements of ballet. Data collection for each participant took approximately 45 minutes.

4.2.3 Jumping tasks

Following a self-directed warm up and sensor attachment, the dancers performed a series of bilateral and unilateral ballet specific jumps (Appendix G). The tasks selected were performed in progressions that followed a typical ballet class format, i.e., jumps with bilateral landings, followed by jumps with unilateral landings. The number of repetitions of each task is presented in Appendix G and is also reflective of performance within a normal ballet class. All unilateral tasks were repeated on both lower limbs.

4.2.4 Data processing

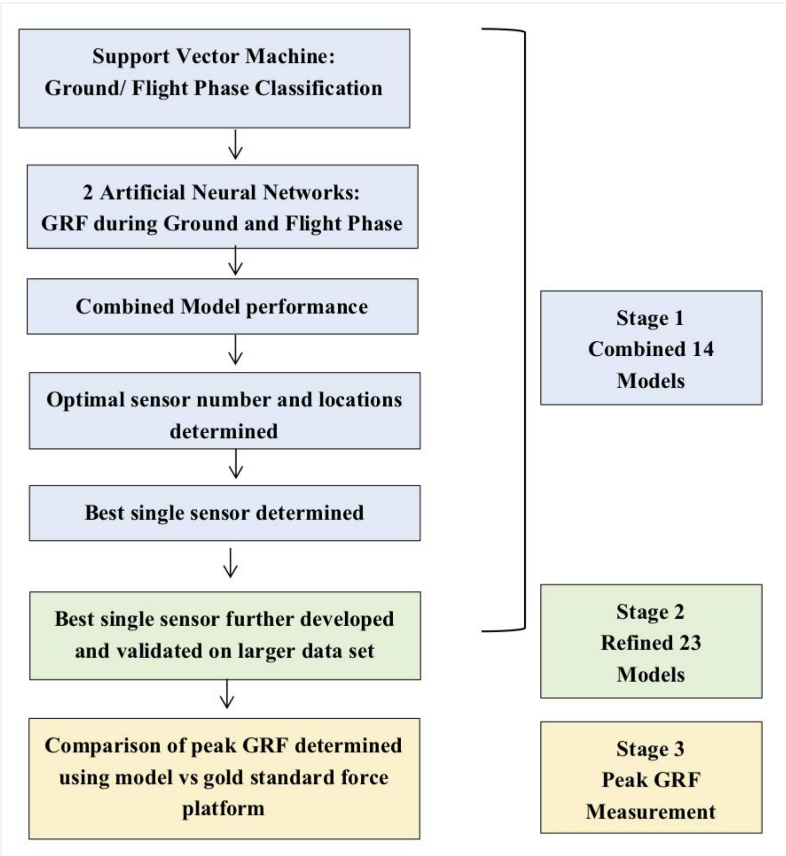
Following data collection, ActiLife software (Version 6.13.3) was used to output date-time stamped files of each wearable sensor's raw data: including tri-axial accelerometer, gyroscope and magnetometer outputs. Force platform data were down-sampled to 100 Hz to match IMU data. Both force plate and acceleration data were normalised to G-force (Gs). A customised LabVIEW program (National Instruments, Austin, Texas, USA) was designed to allow semi-manual time synchronisation of wearable sensor data with force platform data. For this purpose, a single reviewer visualised the sum of the residuals of the sacrum sensor accelerometer data with the force plate data to align and check for synchronisation. Following time synchronisation, the program outputted a collated file of all wearable sensor and force platform data for each task.

4.2.5 Machine learning model development and validation

While data were collected on 30 dancers, wearable sensor data from 7 of the dancers had issues with hardware malfunctions. This was recognised when data was downloaded and visually inspected after data collection. Hardware malfunction issues included sensors not being accepted by the docking station to download data and sensors breaking during data collection and not collecting data. Therefore only 23 of the dancers had data that could be used in the development of the machine learning model. Of these 23 dancers, 14 had data which were deemed adequately synchronised across all 6 sensors, allowing for exploration of multi-sensor models. Synchronisation issues were caused by a manufacturer fault in this brand of sensors, which can result in a between-sensor time shift. As a result, some sensors could not be synchronised due to large time differences between both the other sensors and the force platform. Adequate synchronisation of sensors was determined via visual observation of a single researcher, by alignment of the peaks of acceleration data, and matching the periods between these peaks.

Visual inspection of the data revealed that the magnetometer raw data was unstable and not representative of the dancers' movement, thus this data was not utilised. Only the accelerometer outputs were used in the development of the models. Gyroscope data was not used in the development of the model to avoid having too much data that was similar to each other, where acceleration is related to velocity, and is also more closely related to force. The model was developed in a number of stages, with the final goal being to achieve a model capable of estimating peak GRF. The stages of development are demonstrated in Figure 4.2, and described below (sections 4.2.5.1 – 4.2.5.3)

Figure 4.2
Flow chart demonstrating model development and validation process and model architecture



4.2.5.1 Stage 1: Initial model development and evaluation

Based on initial experimentation, two pilot model designs were developed using data from 14 of the dancers; one for unilateral landings, and one for bilateral landings. The models were initially trained on 12 dancers (training set) and evaluated on the remaining two (test set). Model architecture is shown in Figure 4.3. The models incorporated a support vector machine (SVM) for flight and ground phase classification with separate artificial neural networks (ANN) for the GRF estimation during each phase. The models were constructed so that the final output model only required single data points and no historic points, thus GRF could be predicted for each data point individually, allowing for the potential of real-time GRF estimation.

4.2.5.1.1 Support vector machine to classify ground and flight phases

The SVM was developed using a gaussian kernel function, to determine if a data point was classified within the flight or ground phase of the jump. The input for the SVM was the vector magnitude of the acceleration data from the IMUs, measured in Gs at 100 Hz for the period of the activity. During the ground phase, the segment accelerations were coupled to the GRF, whereas during the flight phase the GRF determined by the force platform is reduced to zero, while the segment accelerations are not. Segment accelerations refer to the acceleration vector of segments of the body such as the torso, thigh or shin. Therefore, a data point was assigned a ground phase label if the GRF recorded by the force plate was greater than 0.05 BW, and assigned a flight phase label if it was less than 0.05 BW.

An equal number of data points for every type of jump performed by each dancer were sequentially arranged, before being rearranged randomly using the MATLAB Random Number Generator (MathWorks, Inc., MA, USA), to produce an overall training set. As the data was collected at 100 Hz, a data point is defined as a time period of data that is 1/100th of a second in duration. The first 500 data points from the overall training set were taken to train the SVM, with a 5-fold cross validation process used, allowing for selection of the best-performing model with a smaller training set. The first 200 data points from the test set were then used to assess the performance of the SVM. A reduced sample was decided upon due to the reduced data requirements of a SVM, requiring smaller training and test data, and to prevent the occurrence of overfitting. Additionally, the smaller test set was used to enable more efficient training and testing of the models, given the large number of models being developed. Overfitting is when a model corresponds too closely or exactly to a particular data set and, therefore, may not be able to predict future observations reliably. Within the context of machine learning for wearable sensors and human movement, this can occur due to a data set which does not provide sufficient variability of movement (i.e. is trained on a set of data that is all very similar, thus the model learns only to recognise these patterns) (Krawczyk, 2016).

To evaluate SVM classification accuracy for each possible sensor combination, confusion matrices were constructed using the percentage of data points that were correctly predicted, for both unilateral and bilateral jumps.

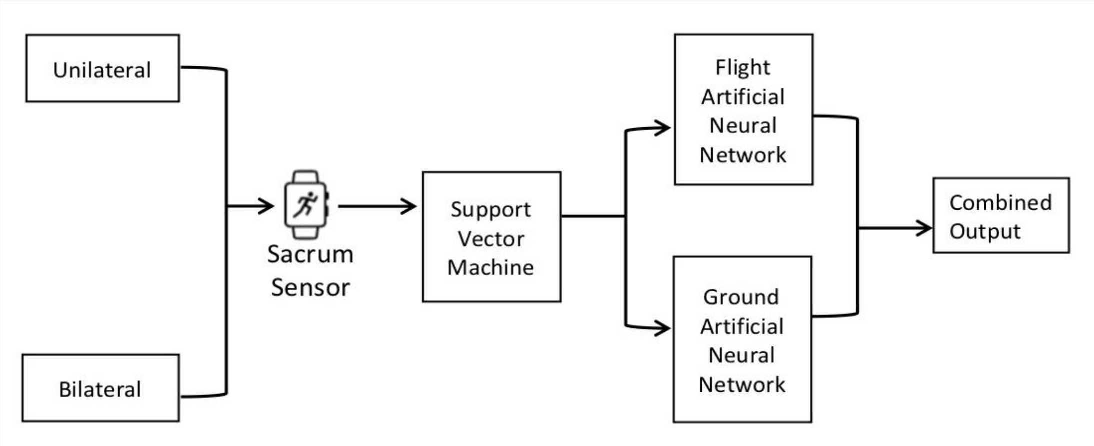
4.2.5.1.2 Artificial neural networks (ANNs) to estimate ground reaction force during ground and flight phase

Separate ANNs were developed; one for the ground phase and one for the flight phase of the jump. Optimal ANN architecture was determined using an iterative loop, to determine which number of neurons in each hidden layer resulted in most accuracy when all 6 sensors were used. For the flight phase, only 1 hidden layer was assessed, and for the ground phase both single and double hidden-layer networks were investigated. Single and double hidden-layer networks with a lower bound of 1 and an upper bound of 35 in each layer were explored when determining the hyperparameters. All models were trained starting with randomly generated weights.

4.2.5.1.3 Combined 14 models to estimate GRF across whole jump activity

The SVM and two ANNs were combined in 2 models, 1 for bilateral landings and 1 for unilateral landings. Separate models were used for each type of landing to improve accuracy due to the differences between bilateral and unilateral landings. In each individual model, once a data point was classified by the SVM as being within the ground phase or the flight phase of the jump, it was fed into the corresponding neural network, as demonstrated in previous reporting (Leporace et al., 2015). This structure allowed for each individual data point to be introduced to the machine learning model to produce an estimation of GRF profile across the whole activity. The model architecture is shown in Figure 4.3.

Figure 4.3
Model architecture



To evaluate the combined model, incorporating the SVM and both ground- and flight-phase ANNs, the GRF estimations across the total GRF curve were compared with force platform 'gold standard' GRF using RMSE, as well as Pearson's correlation coefficients to provide indication of standardised fit. The total GRF curve of each jump was considered including both the flight phase and subsequent ground phase.

4.2.5.1.4 Determination of optimal sensor number and locations

The performance of all sensor combinations was compared by utilising a SVM, an ANN and the Combined 14 Models for each sensor combination. For both unilateral and bilateral jumps, 63 models were developed, 1 for each different combination of sensors (all 6 sensors, all combinations of 5 sensors, all combinations of 4 sensors, etc.). SVM performance was evaluated using a confusion matrix for classification accuracy. ANN and Combined 14 Model performance was evaluated by comparison with force platform GRF across the whole jump activity using RMSE and Pearson's correlation coefficients. This was determined using a leave-two-out-cross validation approach, where the model was trained on 12 dancers and evaluated on the remaining two, and this was iteratively repeated on all combinations of two dancers (total of 91 combinations, yielding a total of 11,466 models trained and tested (63 [possible sensor combinations] × 91 [combinations of dancers] × 2 [unilateral/bilateral]). The 10 best possible combinations (number and locations) of sensors were saved. The leave-two-out cross validation approach was used to allow greater generalisability of the model given the smaller sample size. The best single-sensor model based on location was identified for both unilateral and bilateral jumps. The best single-sensor model was determined by looking at the SVM, ANN and

Combined Model results together and determining which single-sensor location performed with greatest accuracy. Additionally, one of the top performing models from the leave-two-out-cross validation for this single sensor was selected to be integrated into a user-friendly program to use for Stage 3 of this development.

4.2.5.2 Stage 2: Refinement and evaluation of single sensor models using a larger sample

Single sacral-sensor models for both the bilateral and unilateral jumps were refined using data from 23 dancers. The model was developed using a leave-one-out-cross validation where it was iteratively trained on 22 dancers' data and evaluated for the remaining 1 (total of 23 combinations) (Hendry, Chai, et al., 2020).

To evaluate the performance of the Refined 23 Models, the average RMSE and correlation coefficients were determined for the GRF profile across the jump activity in comparison with the gold standard force platform GRF profile. One of the top performing models was selected to be integrated into a user-friendly program to use for Stage 3 of this development.

4.2.5.3 Stage 3: Validation of Combined 14 Models and Refined 23 Models to determine peak ground reaction force using single sensor

For both the 14 dancer and 23 dancer single-sensor models, one of the top-performing models was selected to be integrated into a user-friendly MATLAB (MathWorks, Inc., MA, USA) program to use for peak GRF output (maximum value within the ground phase) for a selection of trials for each of the 23 participants. Bland–Altman plots were constructed to determine the level of agreement between the machine learning models and the gold standard force platform peak GRF values.

4.3 Results

4.3.1 Stage 1: Support vector machine, artificial neural network and Combined 14 Models performance

The performance of the SVM when all 6 sensors were used demonstrated an average 87.8% degree of accuracy for unilateral jumps and 80.8% for bilateral jumps. Using all 6 sensors, the Combined 14 Models, trained and tested on 91 combinations of dancers, demonstrated an average RMSE of 0.24 BW for unilateral landings and 0.21BW for bilateral landings, with average correlation coefficients of 0.96 and 0.98, respectively.

4.3.2 Stage 1: Determination of optimal sensor number and locations

The performance of the Stage 1 SVMs tended to improve with fewer sensor inputs. This is demonstrated in Table 4.1 which shows the best sensor location combinations for 1 to 5 sensors. The sacral sensor had the highest accuracy of any single sensor. Confusion matrices for the single sacral sensor are demonstrated in Figure 4.4.

Table 4.1
Support vector machine (SVM) performance for best sensor location combinations for each number of sensors

	Unilateral		Bilateral	
# sensors	**Best Combination**	**% correctly predicted**	**Best Combination**	**% correctly predicted**
1	Sx	89.3	Sx	83.6
2	Sx, LSh	88.5	Sx, Tx	82.8
3	Sx, Tx, RSh	88.3	Sx, LTh, RTh	78.5
4	Sx, Tx, LSh, RSh	86.3	Sx, Tx, LTh, RTh	82.3
5	Sx, Tx, RTh, LSh, RSh	88.5	Sx, Tx, LTh, RTh, RSh	76.5

Key:
Sx- Sacrum, Tx- Thoracic, LTh- Left Thigh, RTh- Right Thigh, LSh- Left Shin, RSh- Right Shin

Figure 4.4
Confusion matrices for support vector machine performance with single sacrum sensor

Unilateral

	True Positive	True Negative
Predicted Positive	61.5%	9.5%
Predicted Negative	3%	26%

Bilateral

	True Positive	True Negative
Predicted Positive	46%	10.7%
Predicted Negative	6.3%	37%

The performance of the top 10 performing sensor combination Stage 1 ANNs and Combined 14 Models is shown in Table 4.2.

Table 4.2
Artificial neural network (ANN) and Combined 14 Model performance of top 10 performing unilateral and bilateral jump models ranked by degree of accuracy from most to least accurate

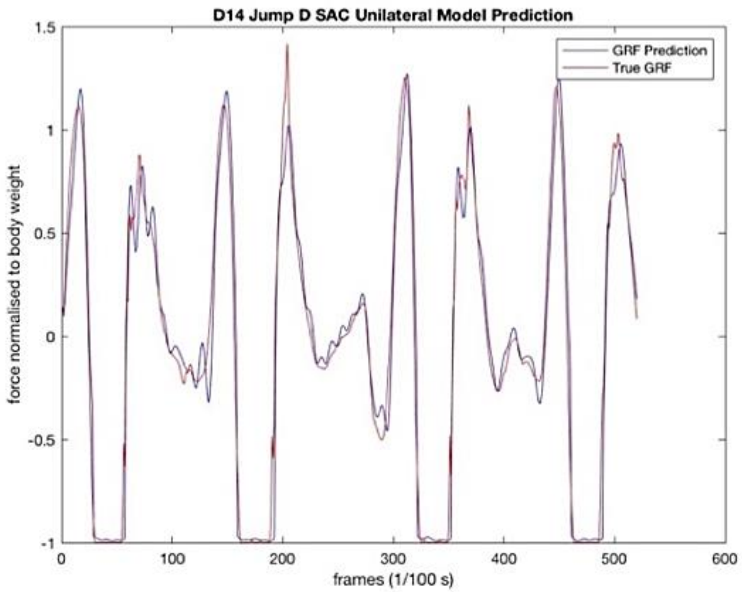
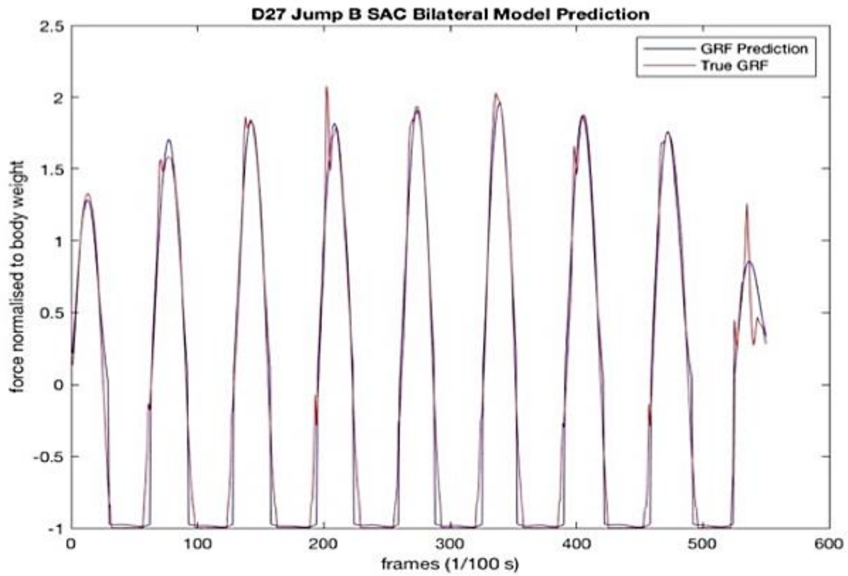
Sensor Combinations	Flight phase (ANN1) RMSE (BW) mean	Ground phase (ANN2) RMSE (BW) mean	Combined (flight and ground phase) RMSE (BW) mean	Correlation coefficient mean
Unilateral				
Sx, Tx, LTh, RTh, LSh	0.05	0.27	0.24	0.96
ALL	0.05	0.28	0.25	0.96
Sx, Tx, LTh, RTh	0.05	0.28	0.25	0.96
Sx, Tx, LTh	0.05	0.28	0.25	0.96
Sx, Tx	0.05	0.28	0.25	0.96
Sx, LSh, RSh	0.05	0.28	0.25	0.96
Sx, LTh, RTh, LSh, RSh	0.05	0.28	0.25	0.95
Sx, LTh, RTh	0.05	0.28	0.25	0.95
Sx	0.05	0.29	0.25	0.95
Tx	0.05	0.40	0.35	0.90
Bilateral				
Sx, Tx	0.04	0.26	0.20	0.99
Sx, Tx, LTh, RTh, LSh	0.04	0.26	0.20	0.99
Sx, Tx, LTh	0.04	0.27	0.21	0.98
All	0.04	0.27	0.21	0.98
Sx, Tx, LTh, RTh	0.05	0.29	0.22	0.98
Tx, LTh, RTh, LSh, RSh	0.04	0.31	0.24	0.98
Tx, RTh, LSh	0.04	0.31	0.24	0.98
Sx, LTh, RTh	0.04	0.31	0.24	0.98
Sx	0.04	0.32	0.24	0.98
Tx	0.04	0.31	0.24	0.98

Key:
Sx- Sacrum, Tx- Thoracic, LTh- Left Thigh, RTh- Right Thigh, LSh- Left Shin, RSh- Right Shin
ANN1- Flight Artificial Neural Network, ANN2- Ground Artificial Neural Network, RMSE- Root Mean Square Error, BW- Body Weight

4.3.3 Stage 1: Combined 14, best single-sensor models

Considering the performance of the model overall, it was determined that the best single-sensor model was the sacrum sensor, with an RMSE of 0.25 BW for unilateral landings and 0.24 BW for bilateral landings, with a correlation coefficient of 0.95 and 0.98, respectively. Considering both the SVM and the Combined 14 Model results this was also considered the best sensor combination overall. Examples of the GRF profile output by the force plate and the best single sensor model are shown in Figure 4.5.

Figure 4.5
Outputs from unilateral and bilateral models—ground reaction force (GRF) profiles

Unilateral model example	Bilateral model example
	

4.3.4 Stage 2: Refined 23 Models

The accuracy of the Refined 23 Models' capability to estimate the GRF profile, accounting for all 23 dancers' data, is demonstrated in Table 4.3.

Table 4.3
Accuracy of final model estimation of Ground reaction force (GRF) across complete curve

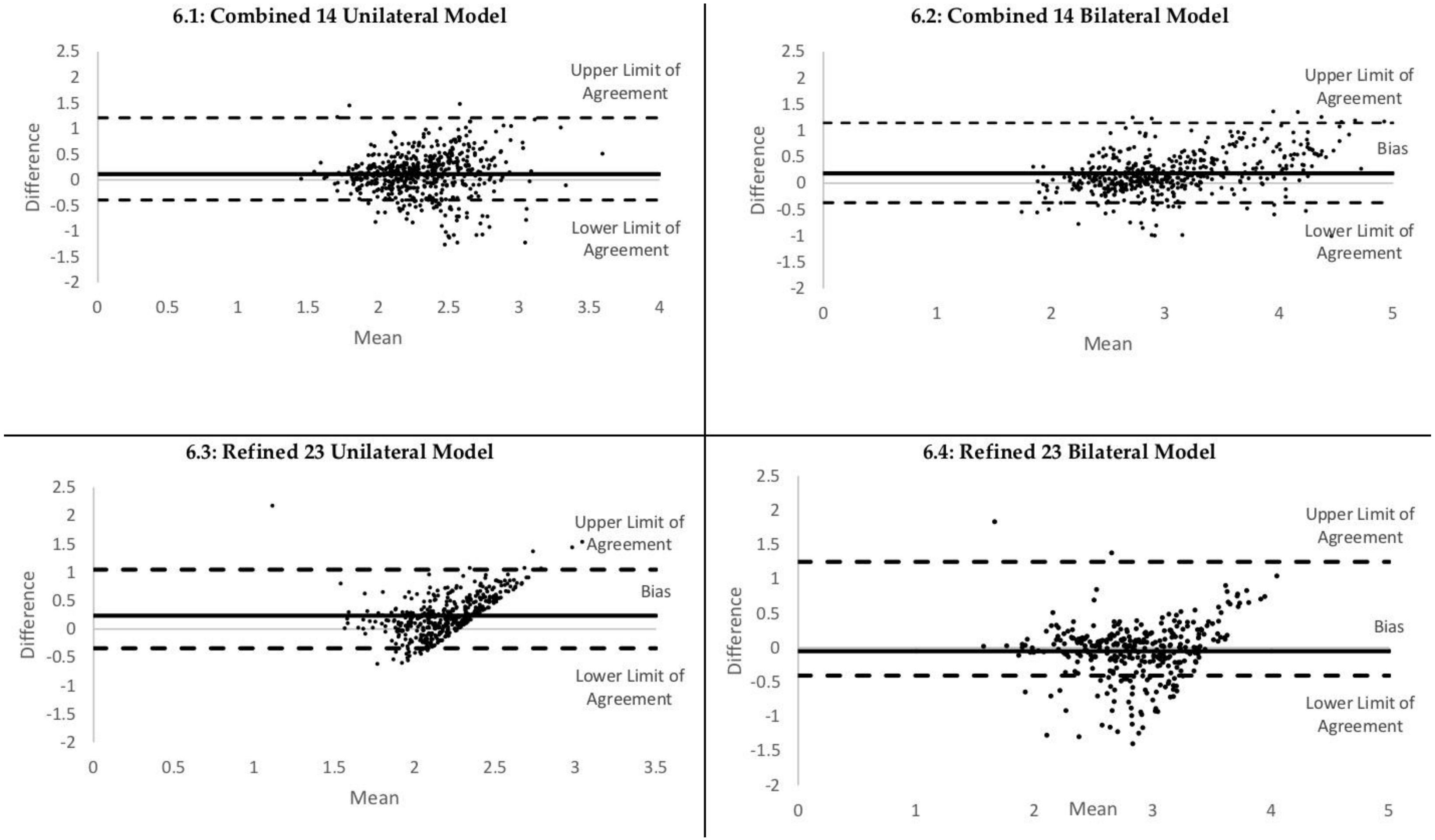
Model	**SVM to identify flight or ground phase accuracy (%)** *mean (range)*	**Flight phase (ANN1) RMSE (BW)** *mean (range)*	**Ground Phase (ANN2) RMSE (BW)** *mean (range)*	**Combined (flight and ground phase) RMSE (BW)** *mean (range)*	**Correlation coefficient** *mean (range)*
Unilateral	83.17 (69.93–92.66)	0.05 (0.03–0.06)	0.30 (0.19–0.46)	0.42 (0.22–0.61)	0.80 (0.55–0.97)
Bilateral	84.06 (75.40–95.59)	0.04 (0.02–0.05)	0.27 (0.18–0.53)	0.39 (0.25–0.67)	0.92 (0.71–0.98)

4.3.5 Stage 3: Combined 14 Models and Refined 23 Models' ability to determine peak GRF

The best bilateral and unilateral model determined for the Combined 14 Models and Refined 23 Models was evaluated. The mean (SD) peak GRF as determined by the force platform was 2.35 BW (0.38) for the unilateral jumps and 3.13 BW (0.72) for the bilateral jumps. The mean (SD) peak GRF for the Combined 14 Models was 2.24BW (0.35) for the unilateral model and 2.95 BW (0.58) for the bilateral model. For the Refined 23 Models the mean (SD) peak GRFs were 2.12 (0.20) and 3.28 BW (0.62), respectively. The Bland–Altman plots are demonstrated in Figure 4.6.

Figure 4.6

Bland-Altman plots for peak GRF estimation performance



4.4 Discussion

The overall aim of this study was to validate the estimation of peak GRF from wearable sensor data during dance jumping tasks against gold standard force plate data. This aim was achieved through a multistage approach to development. The model architecture was developed within the first stages using 14 dancers, and evaluation of the different sensor numbers and locations determined that a single sacrum-mounted sensor performed with the same accuracy as the multi-sensor models for both unilateral and bilateral jumps. Interestingly, the second-stage model, developed on a larger sample, yielded poorer accuracy.

Regardless of the number and locations of sensors, all developed models in Stage 1 performed well. All of the top 10 sensor combinations for the Combined 14 Models demonstrated an RMSE of less than 0.35 BW for the unilateral models and 0.24 BW for the bilateral models. This model performance was superior to previous machine learning model developments for GRF using data from 3 sensors on 8 participants to predict GRFs during running (average RMSE of 0.40 BW) (Wouda et al., 2018). Additionally, the accuracy demonstrated in the current was similar to that shown for a knee joint reaction force machine learning model, developed on data from 13 participants (Stetter et al., 2019). Their model achieved an average RMSE of 16.7% for unilateral jump landings and 25.9% for bilateral. Table 4.4 demonstrates a tabulated comparison of the results of the existing study compared with previous reporting. Additionally, the single sacrum sensor Combined 14 Models and Refined 23 Models were capable of detecting peak GRF with a similar mean difference between the model and the gold standard force platform. For the single sacrum sensor unilateral Combined 14 Models the mean difference was 0.11 BW and for the single sacrum sensor bilateral Combined 14 Models the mean difference was 0.19 BW. Similarly, for the single sacrum sensor unilateral Refined 23 Models the mean difference was 0.22 BW and for the single-sacrum sensor bilateral Refined 23 Models it was 0.18 BW. These mean differences were slightly higher than that demonstrated by Wouda et al, where the peak GRF mean difference demonstrated between their model and the force platform was 0.10 BW (Wouda et al., 2018). Overall the current study’s findings suggest that the application of a machine learning approach to wearable sensor dancer for GRF estimation during complex athletic jumping activities, provides an accurate means to field-based estimation of GRF.

Table 4.4
Comparison of findings with other studies

Reference	Participants used for development	Number of sensors	Sensor locations	Machine learning approach	Movement tasks	Variable measured by machine learning approach	Average RMSE
Current Study	23 female dancers (Stage 1 developed on 14 dancers, stage two on 23)	All combinations of 6, 5, 4, 3, 2 and 1 sensors. Demonstrated a single sensor approach in final reporting	Bilateral thigh, bilateral tibia, sacrum, thoracic	SVM and ANN	Unilateral and bilateral jumps	Resultant GRF across all data points of GRF profile, peak GRF.	Stage one development: Unilateral: 0.25 BW Bilateral: 0.24 BW Stage two development: Unilateral: 0.42 BW Bilateral 0.39 BW
(Wouda et al., 2018)	8 runners	3 sensors	Bilateral leg, sacrum	ANN	Running	Vertical GRF across all data points of GRF profile, peak GRF	0.40 BW
(Johnson et al., 2019)	Did not specify	1 sensor	Sacrum	Convolutional Neural Network	Running and side stepping	3-dimensional GRF across all data points of GRF profile	19.7% (sidestep)–29.7% (run) of BW
(Stetter et al., 2019)	13	2 sensors	Thigh and shin	ANN	Running, running with turn, sprint start, full stop, side cutting maneuvers, walking, walking with turning, unilateral and bilateral jumping and landing	3-dimensional knee joint reaction force	Vertical: 19.1% of BW Anterior/ Posterior: 21.8% of BW Medial/Lateral: 38% of BW

The Combined 14 Models development revealed the most accurate number of sensors and sensor locations for the unilateral model consisted of 5 sensors, and the second most accurate of all 6. Interestingly, the single sacrum sensor was almost as accurate as a combination of multiple sensors, with the same RMSE, of 0.25 BW as these multi-sensor combinations. For the sacrum bilateral model, the difference between the best performing multi-sensor combination (sacrum and thoracic sensor) was only 0.04 BW. Additionally, regardless of whether a multi-sensor or single-sensor model was used, there was excellent correlation between the machine learning models and gold standard force platform (0.95 and 0.96, respectively). A similar difference existed for the bilateral model, which displayed stronger correlation than the unilateral. This was unexpected, as previous literature has suggested that for machine learning applied to wearable sensors and human movement, multiple sensors are advisable, as it can provide the highest recognition rate (Attal et al., 2015). The results of the SVM suggest that, within the current study, the use of more sensor locations resulted in poorer classification of ground or flight phase, thus effecting the rest of the model. To date, no other researchers have demonstrated the use of machine learning with a single sensor; only one other study has utilised a single sensor machine learning model for GRF estimation during sidestepping and running (Johnson et al., 2019). There are multiple practical benefits of using a single sensor as opposed to multiple sensors; a single sensor is more affordable, has a reduced athlete and analysis burden, and does not require synchronisation with other sensors, thus reducing overall processing demands.

The best single-sensor location was the sacrum. This was of interest as, currently within the sporting environment the most common location for a single sensor appears to be on the upper back (Chambers et al., 2015; Hulin et al., 2017; McNamara et al., 2015; Rogalski et al., 2013). For example, when sensors are used in team sports for quantification of training volumes and impacts, as part of athlete monitoring regimes, the sensor is most commonly mounted to the upper back (Hulin et al., 2017; Rogalski et al., 2013). While the single thoracic sensor still featured within the top 10 performing sensor combinations in the unilateral model, as found during feature extraction, it had a 0.10 BW higher RMSE than the sacrum sensor, thus was less accurate. Interestingly, the RMSE was not different between sacrum and thoracic mounted sensors in the bilateral model. One other machine learning study has demonstrated the use of a single sacrum sensor, showing an error of up to 29.7% during running, which would equate to approximately 0.7 BW, given that during running the GRF attained can be up to 2.5 BW (Johnson et al., 2019). Thus, the models developed in the present study performed with greater accuracy. A sacrum-mounted sensor is also the most feasible sensor location for the application to dance, conforming to both aesthetic and movement requirements. Within other sports, the results of our study suggest that if sports scientists would like to objectively quantify impact loading, particularly for single limb loading activities as part of athlete monitoring, a sacrum mounted wearable sensor may be more accurate when compared to an upper back-mounted sensor.

When the single sensor sacrum model was further developed in the Refined 23 Models, the mean RMSE increased to 0.42 BW for unilateral jumps and 0.39 BW for bilateral jumps. Additionally, the correlation coefficients also reduced to 0.80 for the unilateral model and 0.92 for the bilateral model. While in theory, a larger data set should improve generalisability of the model and model performance, it is likely that the reduced accuracy of the models seen in the Refined 23 Models is due to overfitting. When the models were trained with the larger data set, the data set was skewed. This is common of normal human movement and one of the common challenges within machine learning (Krawczyk, 2016), where in this case the dancers demonstrated a small number of variable GRF profiles. This was clearly highlighted in the peak GRFs Bland–Altman plots. When peak GRF was output using the Refined 23 Models, the unilateral model did not demonstrate peaks greater than 2.29 BW and the bilateral 4.01 BW, despite the gold standard force platform demonstrating greater values up to 3.85 BW and 5.51 BW for unilateral and bilateral jumps respectively. This cropping of values in the Refined 23 Models was not evident in the Combined 14 Models development. This has not been reported before and, given that increased data have been reported to increase accuracy, is surprising (Krawczyk, 2016). Further exploration of the data set using frequency histograms for the bilateral jumps (see Appendix H), demonstrating the range of GRFs used for training the models in the development of the Combined 14 and Refined 23 Models confirmed this hypothesis. The dancers landed with reasonably consistent GRFs, with the majority of peaks falling between 1.5–2.5 BW for unilateral jumps and 2.0–2.8 BW for bilateral jumps. Furthermore, the Refined 23 Models' data shown in Appendix H appears to be skewed towards smaller GRFs. This was likely due to the nature of the jumping tasks that were utilised, and represented an imbalanced data set (Krawczyk, 2016). Future research aiming to determine peak GRF during athletic tasks could potentially firstly endeavour to train the model with a large range of peak GRFs and also train the model specifically to detect the peak as opposed to the whole curve.

4.4.1 Strengths and limitations

The models developed in this study can be used to estimate the GRF during impact-based activities in the athletic area of dance. While the authors acknowledge that dance is a niche athletic area, this study provides a proof-of-concept that could be easily applied to other sports, thus is highly translatable. The accuracy achieved is promising with a number of strengths. The models were developed using a relatively large sample compared to other studies, and additionally this sample included a range of dance ability thus increasing generalisability of the models. This study was limited to estimation using only IMU acceleration outputs. While the use of only accelerometer potentially reduces processing time and promotes longer battery life in the sensor, it only allows for resultant GRF estimation with no indication of the direction of the forces. Future developments of machine learning algorithms should consider utilising well calibrated magnetometer and gyroscope data to allow for force direction. Furthermore, by accurately estimating the GRF combined with specific segments kinematics, traditional inverse dynamics models could be applied to potentially calculate external joint forces at every joint. Additionally, the ActiGraph Link sensor used in this research was limited to a maximum sampling frequency of 100 Hz. A higher sampling frequency may provide more accurate results but also creates a greater burden of analysis.

Despite the very strong correlations and low RMSE reported for the full GRF profile, the Refined 23 Models demonstrated an overfitting error that led to reduced accuracy in estimation of large peak GRF values during jumping. This suggests that future machine learning endeavours on athletic pursuits with large variability need to manage data carefully to ensure it encompasses the full variety of movement and is normally distributed. Finally, the models developed through the different stages of this research used different validation techniques dependent on the sample size presented for the model. Further research evaluating the most beneficial validation of machine learning models based on sample sizes is needed. Finally, the sensors may not always represent movement of true ‘rigid segments’ as they are fixed to soft tissue and may come loose. This risk was minimised by attaching the sensor with tape, participants wearing fitted clothing and securing clothing away from the sensor where possible to minimise movement artefact.

4.5 Conclusions

The current study demonstrates that the novel application of machine learning to wearable sensor data allows for accurate estimation of peak GRF and the GRF profile during dance-specific jumping tasks. Interestingly, feature extraction testing revealed that a single sensor was capable of predicting GRF with the same degree of accuracy as a multi-sensor model. No previous reports have demonstrated the use of machine learning applied to a single wearable sensor on a sample of this size and with the degree of accuracy shown in this study.

While the results are promising, the development did come with challenges. When the model was trained and tested on a larger sample, the accuracy of the model deteriorated and there appeared to be overfitting of the model, resulting in a cropping of peak forces. This is reflective of an imbalanced data set which is considered typical to normal human movement, and movement that is performed by a highly trained, aesthetic population. Additionally, challenges of hardware malfunctions and synchronisation problems reduced the overall data set that was available for model development.

These results provide scope for the use of a single wearable sensor, combined with machine learning, to accurately estimate near real-time GRF within a dancer's normal training environment. While developed within the niche athletic area of dance, the models developed in this research demonstrate the feasibility of this approach, which could be applied to other lower limb-loading sports and activities, providing a field-based measurement system for biomechanical quantification. This system, and future developments of it, could be used for athlete monitoring, both clinically and in research settings, for the provision of field-based objective quantification of GRF's during training, competition and performance could lead to an improved understanding of musculoskeletal pain conditions.

Chapter Five

5

Study 2B:

Development of a Machine Learning Model for the Estimation of Hip and Lumbar Angles in Ballet Dancers

This Chapter presents findings from Study 2b, describing the development and validation of machine learning models for the estimation of thigh elevation and lumbar spine sagittal plane joint angles during leg lifting tasks, allowing for field-based measurement of movement quality. Findings from this study have been published and are presented verbatim in this chapter. The full reference for the published manuscript is:

Hendry, D., Napier, K., Hosking, R., Chai, K., Davey, P., Hopper, L., Wild, C., O'Sullivan, P., Straker, L., & Campbell, A. (2021) Development of a machine learning model for the estimation of hip and lumbar angles in ballet dancers. *Med Probl Perform Art, 36*(2): 61-71

Ethics approval for this study was obtained from Curtin University Human Research Ethics Office (HRE2017-0185) (Appendix A). A recruitment flier was utilised to recruit participants (Appendix E) and participants were provided with a participant information and consent form which they completed prior to commencing the study (Appendix F).

5.1 Introduction

Hip and low back pain are commonly experienced by ballet dancers (Allen et al., 2012; Swain et al., 2017; Swain et al., 2018; Trentacosta, Sugimoto, & Micheli, 2017). This pain can be highly disabling, resulting in substantial modification to training and time loss from performance (Swain et al., 2018). For example, a systematic review demonstrated hip pain accounted for 17.2% of all musculoskeletal pain conditions reported by 2001 student and professional dancers whose training included ballet (Trentacosta et al., 2017). Similarly the low back is the third most common site of disabling pain in ballet and contemporary dancers, with recent studies finding 38-52% of pre-professional and professional ballet and contemporary dancers report a history of disabling low back pain (Hendry, Straker, et al., 2019; Swain et al., 2018). The majority of hip and low back pain presentations in dancers may be associated with repetitive loading through limb movement (Allen et al., 2012).

Classical ballet choreography often requires the leg to be repeatedly elevated in a range of front, side and back positions that has been shown to require multi-planar hip movement and lumbar spine sagittal movement (Bronner, 2012; Bronner & Shippen, 2015). For example, laboratory studies have reported that female dancers use 92.5° and 95.2° of hip flexion (thigh relative to pelvis) during leg lifts to the front and side of the body (developpe devant and developpe a la seconde respectively, see Table 5.1), and during an arabesque task 23.4° of hip extension and 21° of lumbar spine extension. (Charbonnier et al., 2011) These movements are believed to be linked to hip and low back pain in dancers, however there is no evidence to support this hypothesis. This may be, in part, due to the limitations of current measurement systems. While the optical motion capture systems are considered the gold standard for evaluating joint kinematics, they cannot assess the cumulative exposure of dancers during normal dance training. Thus, a field-based system capable of measuring thigh elevation and lumbar angles may assist to further explore the relationship between large leg lift movements and the development of hip and low back pain in dancers. Recent advancements in small, commercially available inertial measurement unit sensors (IMUs), have opened the possibility of field-based measurement of joint angles and body segment elevation (Teufl et al., 2019; Wouda et al., 2018).

Table 5.1
Description of leg lifting task

Grands battements *(devant, a la seconde, derriere)*	In a controlled large amplitude tossing or throwing action, the dancer flexes at the hip to bring the lower limb with the knee held in extension to the front of the body successively, closing into 5th position each time. The dancer then repeats this movement to the side of the body and then behind the body (hip and lumbar spine extension).	3 repeats of each: 3 directions, right and left
Developpe *(devant, a la seconde, derriere)*	In a slow controlled movement, the dancer lifts the lower limb by flexing the hip while keeping the knee flexed until the hip reaches end range, then extends the knee, to the front of the body. This is repeated to the side and the back.	3 each direction, right and left
Battement Lente *(devant, a la seconde, derriere)*	In a slow controlled movement, the dancer lifts the leg to the front of the body, maintaining knee extension. This is repeated to the side and the back.	3 each direction, right and left

Translations:
devant- to the front, *a la seconde*- to the side, *derriere*- to the back/ behind the body

An IMU typically contains an accelerometer, gyroscope and magnetometer. Joint angles are often derived from data collected by several sensors utilizing a sensor fusion algorithm to estimate segment orientations (Teufl et al., 2019). For example, this indirect measure of orientation has been used to assess sagittal plane hip movement of healthy (non-dancer) participants during a squat using data from the accelerometer, gyroscope and magnetometer of 7 sensors, with a RMSE of 5.4-8.8° when compared to an optical motion capture system (Teufl et al., 2019). However, these methods have a number of limitations. Sensor fusion algorithms require several sensors to determine segment orientation. As well as being costly and increasing processing demands, multiple sensors are burdensome to the dancer and may impede the aesthetic and movement of dancers (Mjosund et al., 2017; Teufl et al., 2019). Furthermore, in field-based use, magnetometer interference and drift can result in reduced sensor accuracy (Vitali et al., 2020). Direct measurement of angular velocity and acceleration may afford analyses of movement quality beyond what is afforded by traditional metrics of range of motion and activity tracking. Recent advances in computational methods, such as machine learning algorithms, have opened the possibility of a different way of processing the raw data to allow for joint angle or body segment elevation estimation.

Machine learning is an application of artificial intelligence which enables systems to automatically learn from experience without being explicitly programmed (Argent et al., 2019). Machine learning is beginning to be applied to develop models that can predict joint kinematics in clinical and sports research (Argent et al., 2019; Wouda et al., 2018). For example, Argent et al.,2019 developed machine learning models using data from either thigh or shin mounted sensors on healthy young adults, to measure hip and knee angles during simple rehabilitation exercises (such as active knee and hip flexion) (Argent et al., 2019). The average RMSE for knee angles ranged from 5.7 to 6.1°, and for hip from 3.6 to 6.1°. Machine learning, in the form of an artificial neural network, has also been applied to the more dynamic, functional task of running. Wouda et al (2018) estimated knee sagittal plane angles, using data from 3 sensors (sacrum and bilateral shin). When their model was trained and tested on the same participant (n=8) the RMSE ranged from 1.4° to 4.4° (Wouda et al., 2018). However training and testing the model on the same individual provides a model of very limited generalizability. When this model was trained on 7 participants and tested on 1, and this was cycled through (leave-one-out cross validation), the accuracy of the model substantially reduced with an RMSE range from 4.8° to 19.5° (Wouda et al., 2018). Recent research has applied machine learning methods to sensors used in ballet for human activity recognition and estimation of ground reaction forces (GRFs) (Hendry et al., 2020a; Hendry, Leadbetter, et al., 2020), however, to our knowledge, no researchers have utilized machine learning to estimate segment angles from sensor data during more complex, functional athletic- or dance-specific tasks. Development of such a model would allow for field-based measurement of kinematics, which could be used to further understand the etiology of hip and lower back pain in dancers.

The aim of this study was to develop a machine learning model capable of estimating a dancer's peak thigh elevation angle (as a measure of commonly discussed leg height construct) and peak lumbar sagittal plane angle during leg lifting tasks, using wearable sensor data. Such a system would provide accurate field-based measurements of dancers' thigh and lumbar spine kinematics, enabling a better understanding of the role of these kinematics as contributing etiological factors in the development of dancers' hip and low back pain.

5.2 Methods

5.2.1 Participants

Thirty female ballet dancers (mean (SD) age: 18.5 (1.7) years) were recruited from dance schools across Perth, Western Australia. To be included in the study, dancers were required to be 16 years or older and participating in a minimum of 6 hours of ballet training per week. Only female dancers were recruited for this study due to higher female participation rates in pre-professional ballet. Both recreational and pre-professional dancers were included in the study to capture a diversity of skill levels and substantial variability of movements to enhance model development. Informed written consent was obtained from all individual participants included in the study. Dancers were excluded from the study if they were currently injured or unwell. This study was approved by the institutional human research ethics committee (HRE2017-0185).

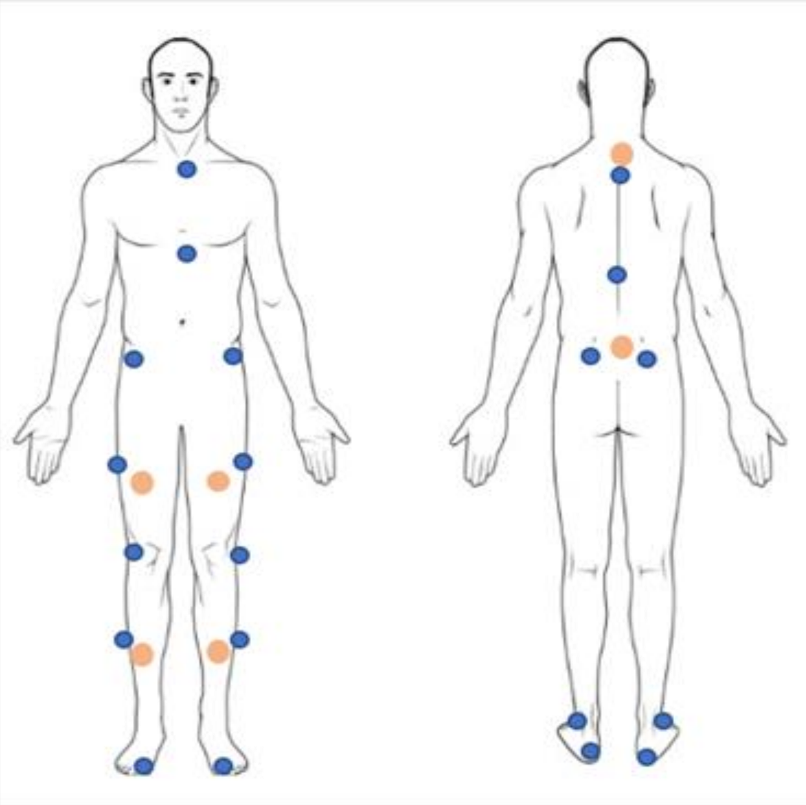
5.2.2 Data collection

Dancers attended a single, 1 hour data collection session at the institutional motion analysis laboratory. Dancers completed a short questionnaire detailing their current dance participation and years of dance experience. Body mass, height and limb measurements (lower limb length, knee width, ankle width) were recorded using calibrated scales (Tanita Corporation of America, Arlington height, Illinois, USA), a stadiometer (Mentone, Victoria, Australia) and a tape measure, allowing for subject calibration with the motion analysis system. Data collection for each participant took approximately 45 minutes.

Three-dimensional motion analysis data were collected using an 18 camera Vicon motion analysis system (Oxford metrics, Oxford, UK) operating at 250 Hz. For this purpose, 21 reflective markers (12.5 mm diameter) were attached to each dancer's lower limbs, pelvis and trunk using low allergenic double-sided tape according to the Plug in Gait lower limb and trunk models (Oxford Metrics, Oxford, UK) (Hendry et al., 2015; Krasnow, Wilmerding, Stecyk, Wyon, & Koutedakis, 2012). Exact marker locations are detailed in Figure 5.1. Segment orientations are detailed in Appendix I.

The dancers also wore 6 ActiGraph Link IMU sensors (ActiGraph Corporation, Pensacola, FL), operating at 100Hz and with the gyroscope and magnetometer enabled. The ActiGraph Link is a small commercially available wearable sensor which includes an on-board tri-axial accelerometer, gyroscope and magnetometer. The sensors were secured to the skin using a single piece of double-sided hypoallergenic tape, and a piece of elasticated hypoallergenic tape covering the sensor (Hendry et al., 2020a; Hendry et al., 2020b). Sensors were placed on the thoracic spine (at the level of T1), sacrum (recommended as this is close to an individual's center of mass) and bilateral thigh and shin (to capture lower limb movement) (Hendry et al., 2020a; Hendry et al., 2020b). Exact sensor located are detailed in Figure 5.1 and in Hendry et al (2020 a & b).

Figure 5.1
Anatomical locations of inertial measurement units (IMUs)



Reflective marker placement for Plug in Gait Model shown in blue and wearable sensor placement shown in orange.

5.2.3 Leg lifting tasks

Following a self-directed warm up and attachment of markers and sensors, the dancers performed a series of 3 types of ballet-specific leg lifting tasks (Table 5.1). The selected tasks were representative of the different types of leg lifting tasks performed within a ballet class and included slow (battement lente and developpe) and fast (grands battements) movements, as well as movements where the dancer lifted their leg up while maintaining knee extension (battement lente, grands battements), and when they unfolded the leg (developpe). All leg lifting tasks were performed to the front, side and behind the body, and performed 3 times on 2 sides (right and left). Dancers self-selected their timing and amplitude of the movement, rather than timing being controlled by a metronome or music, allowing for the model to be trained and tested on diverse data. The relative speed of the movement performed conformed with the specific movement they were performing. The side (right or left leg) that the dancer was lifting was recorded by the researchers for each trial.

5.2.4 Data preparation

The optic motion capture data were collected (250Hz) and processed using Vicon Nexus software (Oxford Metrics, Oxford, UK). This system is known to have only small dynamic reconstruction errors (<2mm) (Merriaux, Dupuis, Boutteau, Vasseur, & Savatier, 2017) and optical motion capture using retroreflective markers is generally the gold standard motion analysis system to derive body segment positions and orientations (Ehara et al., 1997). Optic motion capture data were down-sampled from 250Hz to 100Hz to allow for time synchronization with the sensor data (100Hz). Three output variables were estimated: whether the dancer was lifting the right or left leg, thigh elevation angle and lumbar spine sagittal plane angle. The thigh elevation angle is the angle of the thigh relative to the horizontal, formed using the Z component of a YZY Euler angle decomposition. The change in the rotation sequence was the decomposition that allowed for this. The lumbar spine sagittal plane angle was determined using the Z component from a ZXY Tait-Bryan decomposition of the orientation of the thorax relative to the sacrum. The complete movement profile of each leg lift task was output, as well as the maximum angle achieved during the leg lift (for leg lifts to the front and side) and the minimum angle achieved (for leg lifts to the back, which were primarily extension movements).

The sensor raw data, including accelerometer, gyroscope and magnetometer outputs in all 3 planes, were downloaded using ActiLife software (Version 6.13.3) as date-time stamped files.

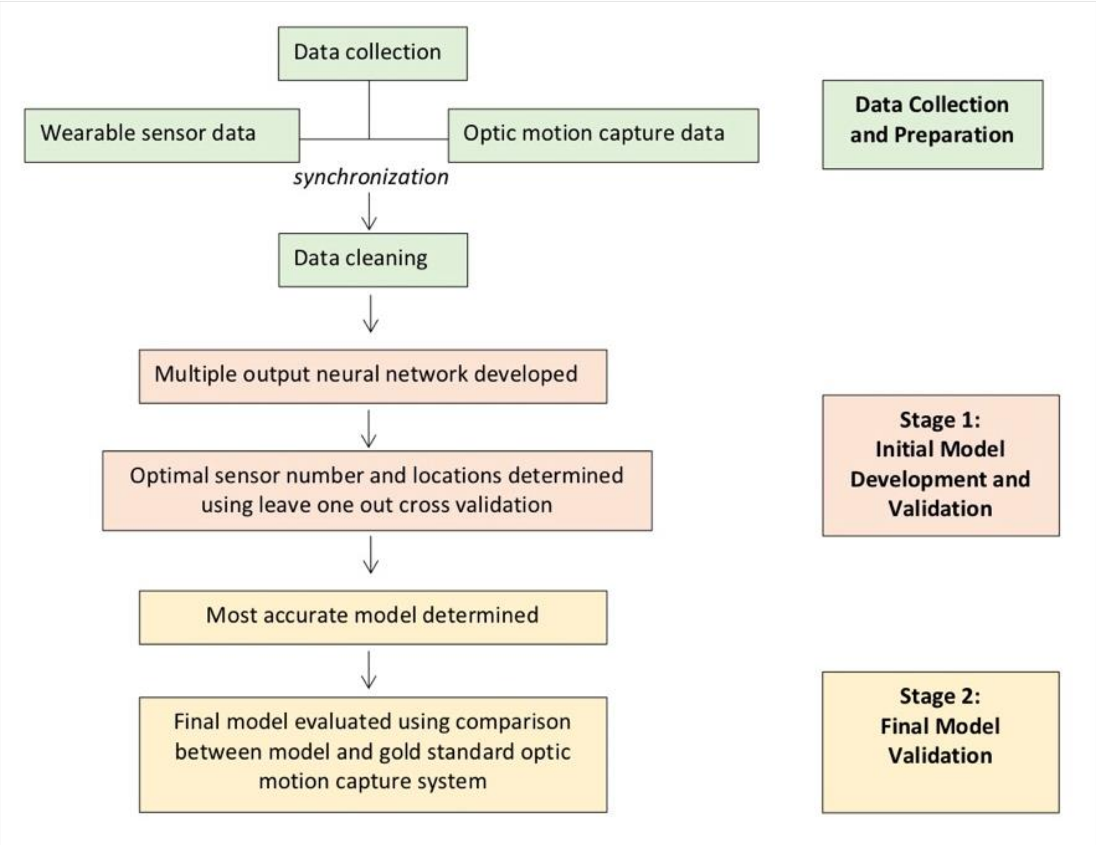
A customized LabVIEW program (National Instruments, Texas, USA) was used to fuse the raw sensor data using a modified Madgwick algorithm (Madgwick, Harrsion, & Vaidyanathan, 2011). The program then used cross-correlation of the sensor orientation quaternions with the orientation quaternions of the corresponding Plugin-Gait segment of the leg that the dancer was lifting, to automatically time synchronize the sensor and optic motion capture data. Synchronization of the sensor and optic motion capture data was visually inspected by 1 of the researchers and manually adjusted where required. Following time synchronization, the program output a collated file of all wearable sensor raw data, the leg that the dancer was lifting (right or left) and the optic motion capture thigh and lumbar spine angle data for each task.

Data from 7 dancers were removed from the dataset due to; sensor hardware malfunctions resulting in sensors not collecting data (n=1), sensor data download malfunctions (n=1), synchronization issues detected during initial synchronization (n=2), and abnormal sensor data detected during data cleaning and preliminary modelling (n=3).

Abnormal sensor data and synchronization issues appeared to stem from sensor drift and misalignment due to magnetometer calibration issues and interference, during synchronization. The remaining dataset (n=23 dancers, 1242 individual movements: 3 types of leg lifts at 2 speeds (slow and fast) in 3 directions (front, side, back) repeated 3 times by each of 23 dancers) was reviewed and cleaned. Outliers, such as movements beyond physiological capabilities, were removed. Specifically, global thigh angles of greater than 150° to the front and back or greater than 160° to the side were removed Additionally, trials where the optic motion capture peak thigh and lumbar spine angles were missing due to occlusion of hip reflective markers were also removed. A total of 24 individual movements removed, accounting for 2% of the data set. The final analytic data set used for modelling was from 23 dancers and 1218 leg lifts.

The models were developed in 2 stages, with the final goal being to achieve a system capable of estimating which leg the dancer lifted, peak thigh elevation angle, lumbar plane sagittal angle. The stages of development are demonstrated in Figure 5.2, and described below (Section 5.2.5).

Figure 5.2
Flow diagram detailing methods



5.2.5 Machine learning model development

5.2.5.1 Stage 1: Initial models development and evaluation

Initial experimentation was performed utilizing neural networks, with a number of different architectures explored (detailed further in Appendix J). A neural network architecture based on long-short term memory units delivered the best results. Long short-term memory units are a class of recurrent neural networks that can effectively learn dependencies between steps in sequence data (Liu, Du, Wu, Wang, & Qiao, 2016).

Removing the magnetometer sensor data improved model performance, so only accelerometer and gyroscope sensor data were used. During data collection, metal equipment in the space may have interfered with the magnetometer's ability to measure magnetic north.

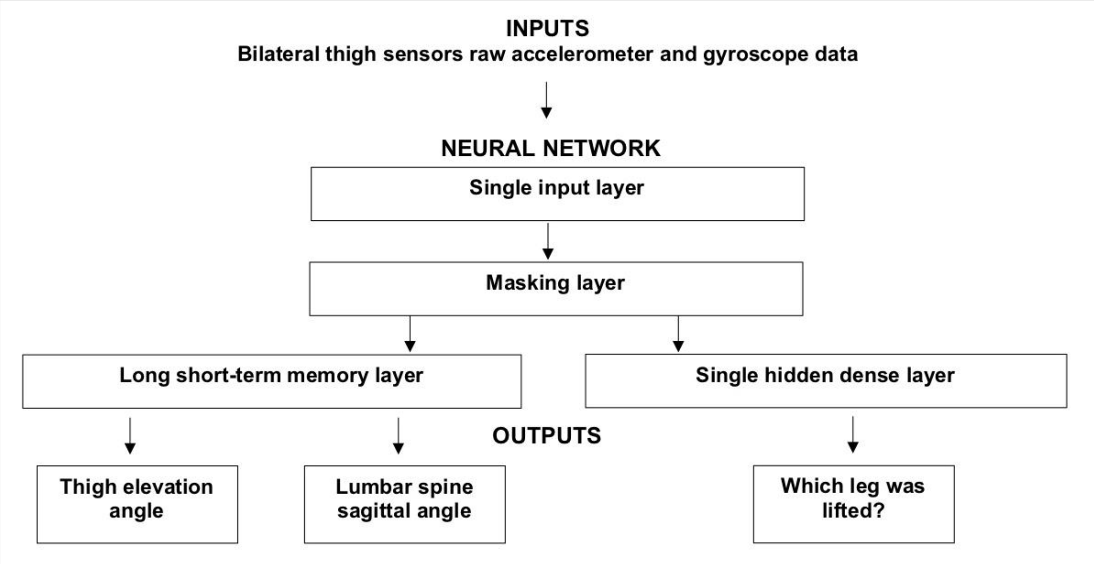
The aim of this stage was to determine which combination of the 6 sensors performed with the greatest degree of accuracy. Models were developed for all possible combinations of 6, 5, 4, 3, 2 and 1 sensor, yielding a total of 63 possible sensor combinations. Each of these models were trained and tested using a leave-one-out cross validation process, where each model was trained on 22 dancers and tested on 1 and this was iteratively cycled through all 23 dancers, yielding a total of 1449 individual models. The RMSE was determined. To allow comparison, the top 10 different sensor combinations and their average RMSE are reported in the results. These experiments were run on a compute instance using Google Cloud's compute engine (n1-standard-4 (4 vCPUs, 15GB memory)).

The model that demonstrated the lowest RMSE from these experiments, used the sensor data from the left and right thigh sensors. This was considered the most accurate model and was used throughout the remainder of the study as the final model.

5.2.5.2 Stage 2: Final model architecture

The final model architecture consisted of a single model architecture (Figure 5.3), requiring the input of the raw triaxial accelerometer and gyroscope data from the 2 thigh sensors with 3 outputs returned; a prediction for side (left or right) and estimations for thigh elevation angle and lumbar spine sagittal plane flexion for each time step.

Figure 5.3
Model architecture demonstrating inputs and outputs of model



The model was capable of producing the described outputs regardless of whether the leg was lifted to the front, side or back. However, the model was not designed to predict if the leg was lifted to the front, side or back. Therefore, investigator knowledge of the direction of the leg lift is required when applying the model. This was decided as this research is part of a larger body of work, which includes human activity recognition models capable of detecting the direction of leg lifting movements (Hendry et al., 2020a). Full details of the final model and definitions of terms can be seen in Appendix J.

5.2.6 Evaluation of final model performance

Model performance was evaluated using a leave-one-out, cross validation method, where the model was trained on data from all participants except 1, which is "held out" as a test data set. This process was iteratively repeated until all participants had served as the test data, thus testing a total of 23 different models. The performance of all 23 models were aggregated for further analysis.

Descriptive statistics (mean and standard deviation) were used to describe the average peak thigh elevation angle and lumbar spine sagittal plane angle across all trials for both the machine learning models and optic motion capture output. The models' ability to determine which leg (right or left) the dancer was lifting, as determined by recording during data collection, in each trial was reported using a percentage of accuracy. RMSE was determined for angle across the entire leg lift movement profile and MAE determined for the peak angle within each individual leg lift movement. The average percentage of accuracy, and average (range) RMSE and MAE determined from the leave-one-out cross validation method was reported. Bland-Altman plots were constructed to further evaluate the models' capability for detecting the peak thigh elevation angle and lumbar spine sagittal plane angles. Pearson's correlation coefficients, between the machine learning model and optic motion capture system, were determined for the peak thigh elevation angle and lumbar spine sagittal plane angles. The performance of the model was determined for all leg lifts (front, side and back directions combined) and each direction of movement individually.

5.3 Results

5.3.1 Initial models performance

The top 10 models developed are demonstrated in Table 5.2. The model with the most optimal performance was the bilateral thigh model.

Table 5.2
Top 10 Performing sensor combinations considering all movement directions (front, side and back)

Sensor Combination	Leg accuracy (%)	Thigh elevation angle RMSE (°)	Lumbar spine sagittal plane angle RMSE (°)
L thigh, R thigh	100%	7.0	5.8
L thigh, R thigh, R shin	100%	7.2	6.0
L thigh, R thigh, L shin	100%	7.3	6.0
L thigh, R thigh, Sacrum	100%	7.4	6.0
L thigh, R thigh, L shin, R shin	100%	7.7	6.1
L thigh, R thigh, R Shin, Sacrum	100%	7.7	6.3
L thigh, R thigh, Thoracic	100%	7.7	6.3
L thigh, R thigh, L shin, Sacrum	100%	7.8	6.1
L thigh, R thigh, L Shin, Thoracic	100%	7.8	6.3
L thigh, R thigh, Sacrum, Thoracic	100%	7.8	6.5

5.3.2 Final model performance

The models were able to correctly determine which leg the dancer was lifting in each trial 100% of the time. When considering model performance specifically to the front, side and back, the average errors were similar (Table 5.3).

Table 5.3
Leave-one-out cross model validation results for thigh elevation angle and lumbar spine sagittal plane angle

	Thigh Elevation Angle		Lumbar Spine Sagittal Plane Angle	
	Average [Standard Deviation] RMSE (Range) (°)	Average [Standard Deviation] MAE (Range) (°)	Average [Standard Deviation] RMSE (Range) (°)	Average [Standard Deviation] MAE (Range) (°)
Front	6.3 [3.2] (2.0-32.0)	5.8 [4.8] (0.0-23.8)	5.0 [2.1] (1.5-12.3)	4.7 [3.5] (0.0-15.6)
Side	6.6 [2.4] (1.8-16.8)	6.1 [5.3] (0.0-26.0)	5.2 [2.0] (1.3-12.3)	5.8 [4.4] (0.0-19.2)
Back	7.4 [3.8] (2.4-33.7)	6.9 [5.8] (0.1-30.8)	6.6 [2.6] (1.8-15.1)	6.6 [5.1] (0.0-30.2)

The average (SD) RMSE for the machine learning models thigh elevation angle estimation across the complete leg lift profile was 6.8° (3.2°) and average MAE for peak thigh elevation angle was 6.3° (5.3°). The average RMSE for the machine learning models lumbar spine sagittal plane angle estimation across the complete leg lift profile was 5.6° (2.4°) and average MAE for peak lumbar spine sagittal plane angle was 5.7° (4.5°). While the averages were relatively small, the range was relatively large (Table 5.3). There was a strong correlation between the machine learning models and optic motion capture for the peak angle values (thigh elevation angle $r = 0.87$, $p < 0.001$, lumbar spine sagittal plane angle $r = 0.96$, $p < 0.001$).

The similarity between machine learning and optic motion capture outputs is further demonstrated in Figure 5.4, showing peak angles for thigh elevation angle (Figure 5.4 [1]) and lumbar spine sagittal plane angle (Figure 5.4 [2]) for leg lifts to the front, side and back.

The Bland-Altman Plot analysis for the peak thigh and lumbar spine sagittal plane angles, during front side and back leg lifts are demonstrated in Figure 5.5. The bias for thigh elevation angle ranged from 1.0° to 3.9° across the 3 directions, with limits of agreement from around -10° to +20°. For the lumbar spine sagittal angle, the bias ranged from -1.8° to 0.2° across the 3 directions, with limits of agreement from around -8° to +25°

Figure 5.4

Optic motion capture and machine learning determined mean (SD) peak thigh elevation angle [1] and lumbar spine sagittal plane angle [2] during leg lifts to the front, side and back

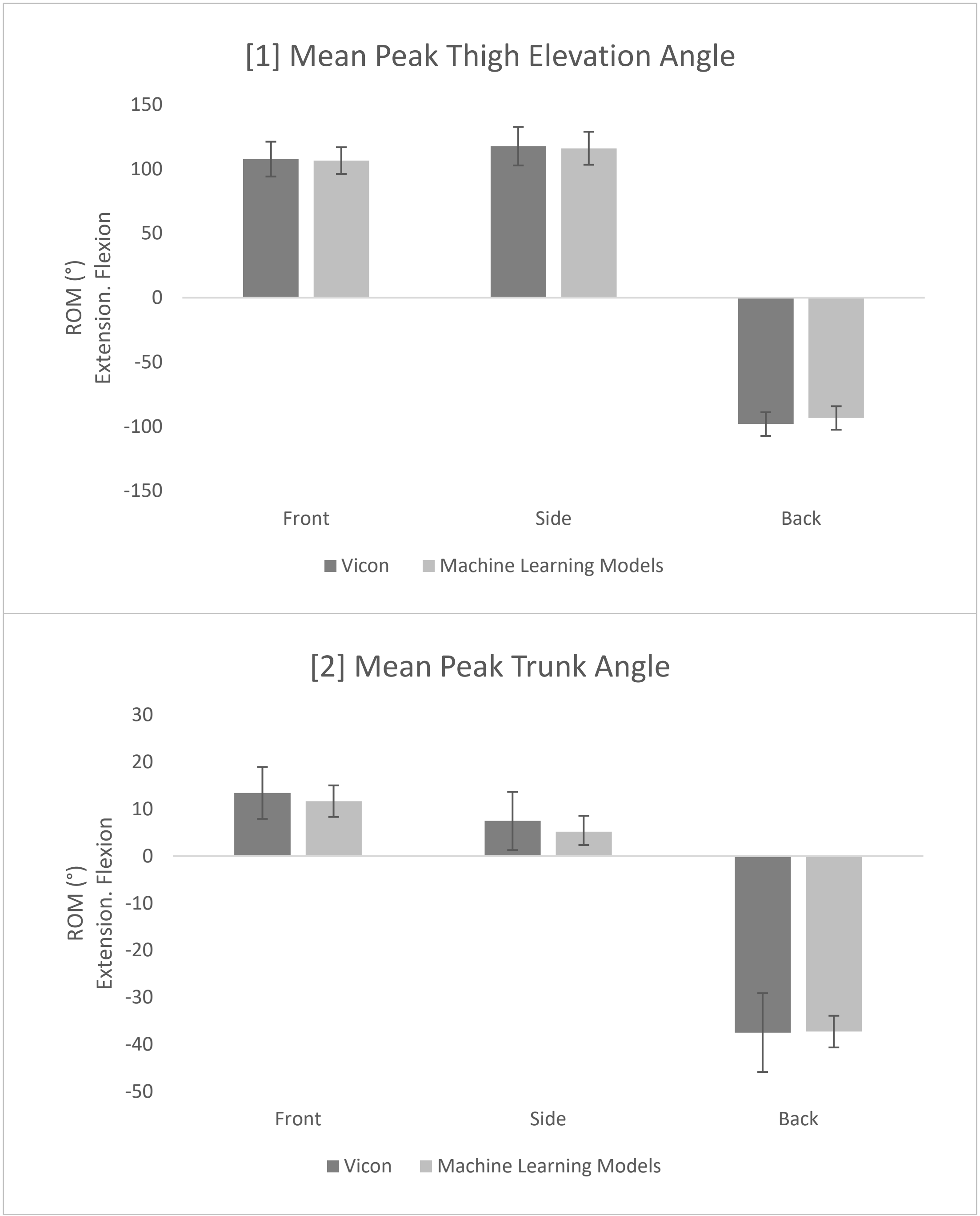
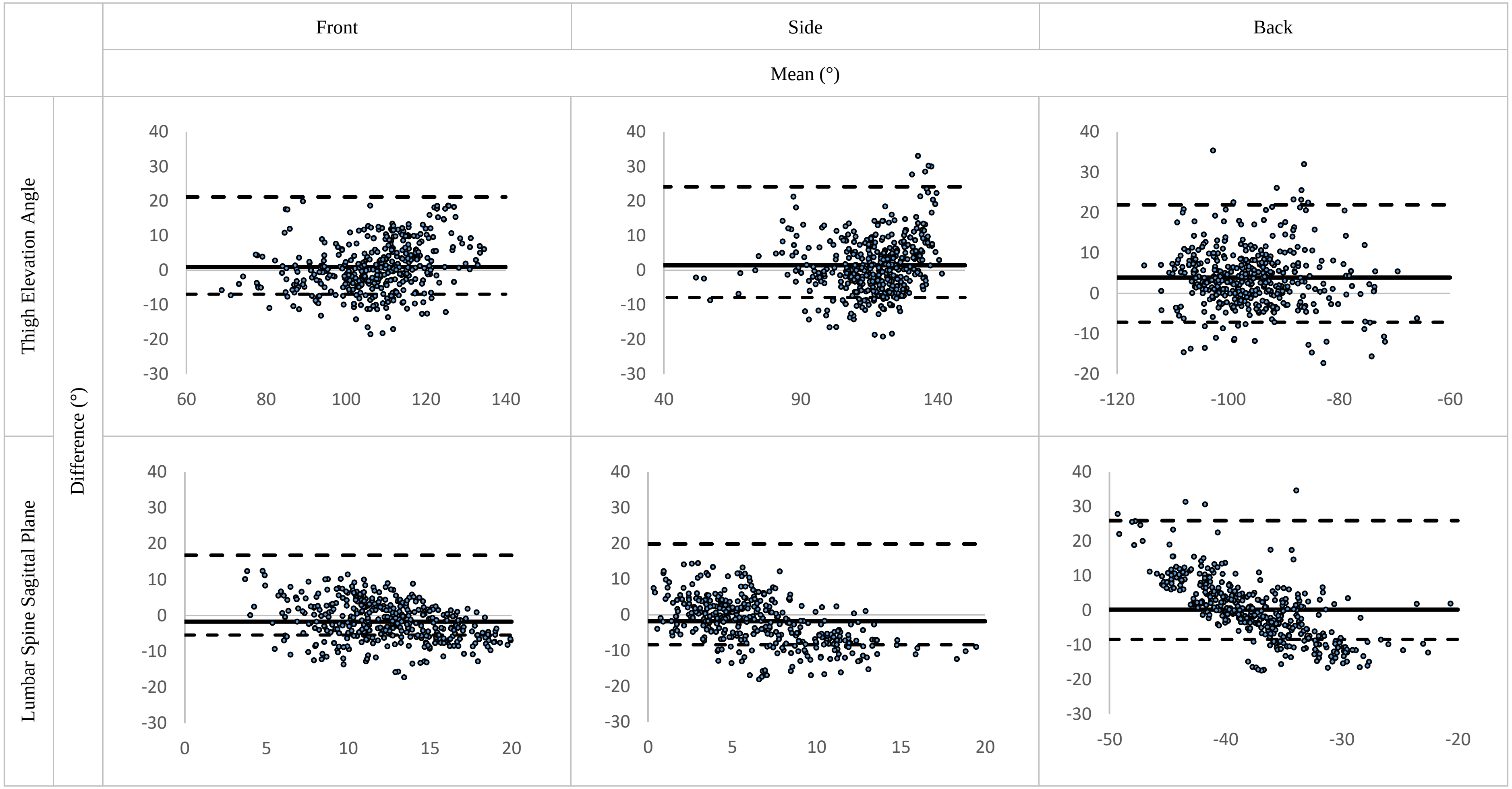


Figure 5.5 *Bland-Altman Plots comparing machine learning model and optic motion capture estimated peak thigh and lumbar angles*



Key: _ _ _ _ _ Upper and lower limits of agreement ▬▬▬▬ Bias

The model with optimal performance, and thus recommended for future use, had 100% leg side prediction accuracy, with an average (SD) RMSE of 5.4° (1.6°) for thigh elevation angle and 4.9° (4.3°) for lumbar spine sagittal plane angle, and average (SD) MAE of 3.9° (2.8°) and 4.6° (2.8°) respectively, with correlation coefficients of 0.85 ($p < 0.001$) and 0.99 ($p < 0.001$) respectively.

5.4 Discussion

Using data from 6 sensors worn by 23 ballet dancers, machine learning models were developed which could accurately identify which leg the dancer was lifting, the global thigh elevation angle and the lumbar spine sagittal plane angle during a range of ballet-specific leg lift tasks. Interestingly, the models which used the data from 2 sensors worn on the left and right thighs yielded the greatest degree of accuracy.

Overall the data used to train and test the models was a typical representation of the range of thigh and lumbar region movement that dancers achieve during leg lifting tasks. Previous literature using optical motion capture has demonstrated that dancers (n=11) achieve a mean hip joint (thigh relative to pelvis) flexion angle (SD) of 88.4° (14.5°) to 95.2° (16.6°) during developpe to the front and the side (Charbonnier et al., 2011). The current study, which estimated thigh global angles, estimated magnitudes greater than those previously reported, i.e. 107.6° for front leg lifts and 117.6° for side leg lifts. While this difference is in part due to the difference in measurements, it may also be due to the tasks that were measured, or the larger sample of dancers. The data from the current study was taken from 3 different leg lifting tasks, incorporating slower and faster movements with different movement trajectories of the lower limb. Recent research has demonstrated that dancers achieve a greater range of motion in faster leg lifting tasks (Mira et al., 2019). Thus the data used to develop the models was representative of a range of different tasks, increasing generalizability of the models. The lumbar spine demonstrated the greatest sagittal plane movement during leg lifts to the back with an average of 37.5° extension. Again, this is greater than that previously reported, where dancers have demonstrated a mean of 21° extension, relative to the reference position (ballet first position), during an arabesque measured using an electrogoniometer (Feipel, Dalenne, Dugailly, Salvia, & Rooze, 2004). Similar to the thigh elevation angles, this study's measurement of less lumbar extension could be due to the range of tasks presented within the current study and differences between measurement systems.

The results of the top 10 sensor combinations during the first stage of model development demonstrated only very small differences in accuracy (less than 1°) between these different combinations. However, the most accurate performing models used only 2 thigh sensors. This was favorable, as a smaller number of sensors reduces processing demands and burden on the dancer (Hendry et al., 2020b). These findings were however surprising, particularly in relation to the lumbar spine angles, where traditional IMU filtering techniques use thorax and sacrum mounted sensors to estimate lumbar angles. The increased degree of accuracy using only 2 thigh mounted sensors in the current study likely reflects the stereotyped, coupled movement between the lower limb and lumbar spine seen during the leg lifting movements used for model development. Potentially, if the dancers performed a wider range of leg lifting tasks, incorporating more varied multi-planar and multi-directional choreography the inclusion of sacrum and thorax mounted sensors would be needed to improve accuracy.

The final models developed in this study performed with an acceptable degree of accuracy and excellent level of agreement with the gold standard motion capture data across all tasks. The average RMSE of 6.8° and MAE of 6.3° for the thigh elevation angle was reported during movements where the dancers were on average lifting their thigh 107.8°. This is superior to the results of 2 comparable studies that applied machine learning to sensor data to estimate lower limb joint angles during running, and active range of movement tasks (Argent et al., 2019; Wouda et al., 2018). During running, a machine learning model developed using data from 3 sensors (bilateral shin and sacrum) placed on 8 participants, demonstrated an average RMSE of 9.3° for sagittal knee angles (Wouda et al., 2018). The average peak knee flexion angles reached by the runners were 39.7° (Wouda et al., 2018). The current research used global angles, whereas the previous research used relative joint angles, which is computationally challenging. Further, a machine learning model for estimation of sagittal plane hip joint angles measured during, uniplanar range of movement tasks (standing hip flexion and extension) demonstrated RMSE's ranging from 3.6-6.1° (Argent et al., 2019). While this error was smaller than that seen in the current study, the machine learning model developed only estimated hip angles, during a single movement task as opposed to estimating both thigh elevation and lumbar spine sagittal angles during multiple tasks. The estimation of the lumbar spine angles in the current study also demonstrated reasonable accuracy (RMSE 5.6°). However, the range of lumbar spine movement is substantially less than that achieved at the hip. There is a growing body of research using wearable sensors and machine learning to study complex movements in their natural environment, such as the study of postural alignment, walking gait, running etc. (Díaz, Stephenson, & Labrador, 2020). The introduction of using machine learning has improved the ability to estimate segmental and joint angles as demonstrated by the accuracy estimates reported in the current study (Díaz et al., 2020). Given the results of the current study and previous studies, this growing area warrants further investigative effort.

Interestingly, the Bland-Altman plot for the lumbar spine sagittal angles for the back leg lifts (Figure 5.5) demonstrated a clear linear relationship between the mean of the optic motion capture and machine learning model and difference between the two, with increasing negative error for smaller amounts of extension. Specifically, when the dancers achieved mid-range lumbar extension during a back leg lift the model performed reasonably well, however when they demonstrated greater or lesser amounts of lumbar extension, the final machine learning model tended to underestimate or overestimate the angle respectively. Interestingly, this clear linear relationship was not evident for the lumbar spine angles in the front and side leg lifts, nor in the thigh elevation angles. This pattern may be, due to the larger ranges of movement achieved by the lumbar spine during leg lifting tasks performed to the back than to the front and side. Potentially, the use of thigh sensor data rather than sensors located on the trunk would also influence this pattern.

While the mean RMSE and MAE were reasonably small, the reported range of errors of both thigh elevation and lumbar sagittal angle were large, with errors ranging from 0° to 34°. However, these larger errors were very infrequent, as demonstrated by the small standard deviations. Rather than individual participants consistently displaying the larger errors, the larger errors were randomly occurred in some trials by different participants (e.g. an individual trial from 1 or 2 participants). Thus, while generally the model performs well sometimes there were large errors. This might be overcome by training on more diverse data sets. Alternatively, in applying machine learning to wearable sensor data, future model developments may consider retraining an established model on each particular application, in the effort to improve model performance. Regardless, the model developed in the current research have sufficient accuracy for group-based analysis, however caution should be exercised with individual analysis.

5.4.1 Strengths and limitations

This study demonstrates the accuracy of a machine learning method to estimate thigh elevation angle and lumbar spine sagittal angle from a diverse range of leg lift tasks representative of those performed in a typical ballet class were used to train the models.

While the leg lifts were taken from a ballet class, similar leg lifting tasks are performed during other dance styles (such as contemporary dance and jazz), therefore potentially increasing the generalizability of the model across multiple dance styles. The data used to develop the models was representative of a cross-section of ballet and contemporary dancers from recreational through to pre-professional levels, thus further enhancing the model generalizability. The sample was also larger than those previously used for machine learning model development for measuring joint kinematics, which may improve generalizability of the models. Further, the models were developed using raw accelerometer and gyroscope data, which are not susceptible to rotational drift, thus reducing potential issues with magnetometer drift and interference.

The study was however limited to a population of female dancers, thus it cannot be determined whether these models would be feasible for use in male dancers, as men anecdotally demonstrate reduced hip and lumbar range of motion compared with their female counterparts. Further, the model was limited to thigh elevation and lumbar spine sagittal plane angles. While thigh elevation angles provide a good indication of leg height, future research should consider the 3-dimensional hip and lumbar angles independently. Given that ballet is characterized by large degrees of transverse plane motion in both the hip and lumbar spine 3-dimensional angles may provide further information on tissue loading and thus pain development. Also, the addition of pelvis-lumbar and pelvis-thigh interaction may also provide further information. However, 3-dimensional angle assessment and addition of pelvis interaction may require increasing the number of sensors. Regardless, this research provides a proof-of-concept that could be easily translated to measure segment angles in other dance-specific and other athletic-specific tasks.

While the model provides estimates of side of leg lift, thigh elevation and lumbar spine sagittal plane angle, it does not identify the direction of the leg lift. As a result, in applying this model in a research or clinical based setting, prior knowledge of whether the dancer is lifting the leg to the front, side or back is required. It is noted, that this manuscript details one component in a more comprehensive machine learning system, which also incorporates a human activity recognition system for identification of leg lifts and direction of leg lift (Hendry et al., 2019). By combining these models, a comprehensive system that can measure both movement quantity (specific training volume) and quality (biomechanical features of thigh elevation and lumbar spine sagittal plane angles) would be possible.

5.5 Conclusion

The final model developed in this research demonstrated excellent accuracy for detecting if the dancer was lifting their left or right leg and mostly acceptable accuracy for estimating thigh elevation angle and lumbar spine sagittal plane angle during ballet-specific leg lifting tasks to the front, side and back.

The findings of the research provide scope for a field-based, near real-time measurement system of joint angles during dynamic, functional dance leg lifting tasks. A minimal sensor, field-based motion capture system provides the capacity to capture a dancer's movement in their normal training environment rather than an artificial and expensive lab environment. This potentially allows for the tracking of dancers' real-world movements over time. Such a system provides new opportunities for researchers and clinicians working within dance medicine. For researchers it enables longitudinal field-based studies to further understand the complex interaction of different factors that may contribute to the development of hip and low back pain in dancers. For clinicians, it allows for a system that can be used within the dancer's normal training environment to assist with the assessment and management of dancers' pain.

Chapter Six

6

Study 3:

Movement Quantity and Quality: How do they Relate to Pain and Disability in Dancers?

This Chapter presents findings from Study 3, where the wearable sensor system developed in Studies 1 and 2 was utilised in a field-based study to explore the relationship of movement quantity and quality with pain and pain related disability in pre-professional dancers. Findings from this study have been submitted to a journal.

Ethics approval for this study was obtained from Curtin University Human Research Ethics Office (HRE2017-0726) (Appendix K). A participant information session was utilised to recruit participants (Appendix L) and participants were provided with a participant information and consent form which they completed prior to commencing the study (Appendix M). The questionnaires used in this study are presented in Appendix N.

6.1 Introduction

Dancers frequently experience musculoskeletal pain, which can be disabling, resulting in the need to modify or cease normal training. Dancers are reported to undertake substantial workloads and perceive large workloads and related fatigue as leading causes of injury (Jeffries et al., 2020; Kozai et al., 2020). In recent years, substantial attention has been placed on quantifying athlete training to assist in understanding the development and experience of pain and disability (Gabbett, 2016; Gabbett et al., 2016; Gabbett & Jenkins, 2011; Gabbett et al., 2014). While athlete monitoring systems are commonly applied in many elite sports, it's only recently emerging within the field of dance, and only assesses *quantity of* dancers' movement (Jeffries et al., 2016; Jeffries et al., 2020; Kozai et al., 2020; L. Lee et al., 2017; Shaw et al., 2021). One recent study has demonstrated that week to week increases in professional ballet dancers' movement quantity is associated with the rate of overuse, time loss injury (Shaw et al., 2021). However, amongst pre-professional dancers, the relationship is less clear. While one study has observed that weekly reported injuries mirror fluctuations in dancers self-reported hours of weekly training, another has found no association (L. Lee et al., 2017; Volkova & Kenny, 2020). The lack of consensus may reflect how movement quantity is measured.

Previous research exploring dancers' movement quantity has focussed on quantifying cumulative workload from activity diaries and schedules, for example daily hours of training (Byhring & Bo, 2002; L. Lee et al., 2017; Shaw et al., 2021; Twitchett et al., 2010; Volkova & Kenny, 2020). However it is recognised that these measures do not capture the movements that dancers perform within their training (Shaw et al., 2021). More recently, wearable sensors have been used to objectively determine the exercise intensity of dancers during their daily training (Jeffries et al., 2016; Kozai et al., 2020). This work has demonstrated that while dancers participate in several hours of training per day, the majority of this time is spent at low to medium intensity exercise (Kozai et al., 2020). Both approaches offer useful insights, however, to date no method exists that provides detailed cumulative workload information such as the number of repetitions of movements that may be provocative of pain, for example the number of jumps or leg lifts performed.

Previous laboratory-based work has also demonstrated that the *quality* of movement may also be associated with pain and disability (Bronner, 2012; Bronner & Ojofeitimi, 2011; Peng et al., 2015). Movement quality refers to the specific biomechanical characteristics of movement and could include aspects such as forces, accelerations, range of movement and variability (Bronner, 2012; Bronner & Ojofeitimi, 2011; Peng et al., 2015). Specifically in dance movement quality, ground reaction force (GRF) during jumps, and thigh elevation angles and lumbar spine sagittal angles during leg lifting tasks, may be an important consideration for pain and disability (Bronner, 2012; Bronner & Ojofeitimi, 2011; Peng et al., 2015). Cross-sectional laboratory studies have shown that during jumping activities dancers achieve peak GRF 2-7 times BW (Fietzer et al., 2012; Harwood et al., 2018; Hendry et al., 2020b; Jarvis & Kulig, 2016; Kulig, Fietzer, & Popovich, 2011). These substantial forces have been associated with the presence of lower limb pain (Peng et al., 2015). Additionally, the large ranges of motion associated with leg lifting tasks have been suggested as contributing to the development of lower back and hip pain (Bowerman, Whatman, Harris, & Bradshaw, 2015; Han et al., 2019; Swain et al., 2018). While considered gold standard, laboratory methods have low ecological validity, thus are more appropriate for once off screening tests as opposed to regular or ongoing monitoring. Regular monitoring of dancers' movement quality may assist in understanding the role of biomechanical demands in dancers' pain.

Recent developments in wearable sensor technology combined with the application of machine learning have allowed for the development of a dance-specific wearable sensor system capable of field-based measurement of movement quantity and quality (Hendry et al., 2020a; Hendry et al., 2020b; Hendry et al., 2021). This system enables field-based studies exploring the relationships of dancers' pain and disability with movement quantity and quality within their naturalistic environment. Large longitudinal studies incorporating ongoing monitoring would enhance understanding of temporal association of changes in movement quality and quantity with musculoskeletal pain, which could be bidirectional. However, to justify larger studies it is important to understand if there are associations between movement quantity and quality within a dancer's normal training when they are experiencing pain, and if the system is capable of detecting these. Thus, this study aimed to estimate the association between pre-professional student dancers' movement quantity and movement quality with (i) pain severity, and (ii) pain related disability over the course of 1 university semester.

6.2 Methods

6.2.1 Study design

This was a field-based study in which repeated wearable sensor-based measures of movement quantity and quality, along with self-reported measures of pain and disability were collected at 4 time points across a 12-week university semester, in the lead up to and following a performance season. This research was approved by the institutional human research ethics committee (HREC2017-0726).

6.2.2 Participants

All female dance students enrolled in the full-time dance courses at an Australian dance training institute (n= 100) were invited to participate in this study. The dancers were provided with an information session about the research and participant information sheets prior to 52 providing consent. Only female students were included in the study, as female and males demonstrate different pain and movement profiles (Mattiussi et al., 2021; Novosel, Sekulic, Peric, Kondric, & Zaletel, 2019). To be included in the study, dancers were required to be a minimum of 16 years old and enrolled in one of the university's full time dance training programs. These programs include extensive training in ballet and contemporary dance. All dancers provided written, informed consent prior to participation.

6.2.3 Data collection

Prior to commencing training for the semester dancers had a brief (1-2 minute) interview with 1 of the researchers, either a qualified physiotherapist or a final year physiotherapy student, both with backgrounds in dance. Demographic and anthropometric information collected by interview included year of training enrolment (first, second or third), age they commenced dancing, dance stream (ballet or contemporary) and height and weight.

Dancers participated in 4 separate days (time points) of data collection. Only 4 days of data collection were scheduled across the 12-week semester period (see Figure 6.1) to minimise dancer burden. Data collected on 10-12 dancers each day, on a day with scheduled ballet technique class.

On each time point of data collection, dancers independently completed a short electronic survey detailing any current pain they were experiencing and were fitted with a previously developed wearable sensor system, capable of field-based movement quantification.

Figure 6.1
Data collection time periods across a university semester

	Normal Classes						Rehearsal/ Production Period			Performance Period	Normal Classes	
Week	1	2	3	4	5	6	7	8	9	10	11	12
	Data Collection 1			Data Collection 2				Data Collection 3				Data Collection 4
Interview	X											
Pain Measures	X			X				X				X
Movement Quantity	X			X				X				X
Movement Quality	X			X				X				X

6.2.3.1 Pain severity and pain related disability

Using the Self Estimated Functional Inability because of Pain Screening questionnaire (SEFIP) (Ramel et al., 1999), dancers reported the anatomical location(s) of their pain in Qualtrics (Qualtrics, Seattle, WA, USA). Dancers were requested to report any pain, irrespective of whether it affected their ability to dance. If the dancer reported multiple locations, they were asked to identify the body region which was bothering them the most. This was considered their most bothersome pain and self-report of pain intensity and pain related disability for that time point was made with reference to this pain location. For each dancer, the location of most bothersome pain could differ over the 4 time points.

For their most bothersome pain dancers were asked to rate the intensity of their pain using a Numerical Rating Scale (NRS) (0-10 scale) (Hjermstad et al., 2011). NRS scores reported at each time point were used as a continuous variable indicating pain severity for aim 1, where higher scores indicated greater pain severity. The NRS has been determined as a reliable and valid measure of musculoskeletal pain (Hjermstad et al., 2011).

Dancers completed the Patient Specific Functional Scale (PSFS) (Abbott & Schmitt, 2014; Nicholas, Hefford, & Tumilty, 2012), whereby they identified up to 3 self-selected important activities that they are unable to do or are having difficulty with as a result of their most bothersome pain. They then scored each activity from 0 to 10, where 0 indicated they were unable to perform the activity at all and 10 indicated that they were able to perform the activity at the same level as before the problem. PSFS scores reported at each time point were used as a continuous variable indicating pain related disability for aim 2. Lower scores indicated greater disability. For each dancer, the nominated activities could differ across the 4 time points. The PSFS has been determined as a reliable and valid measure of musculoskeletal disability (Nicholas et al., 2012).

Additionally, the presence of pain related disability at any of the time points was used to describe the sample. Pain was considered disabling for scores of less than 7 in the PSFS for at least 1 activity.

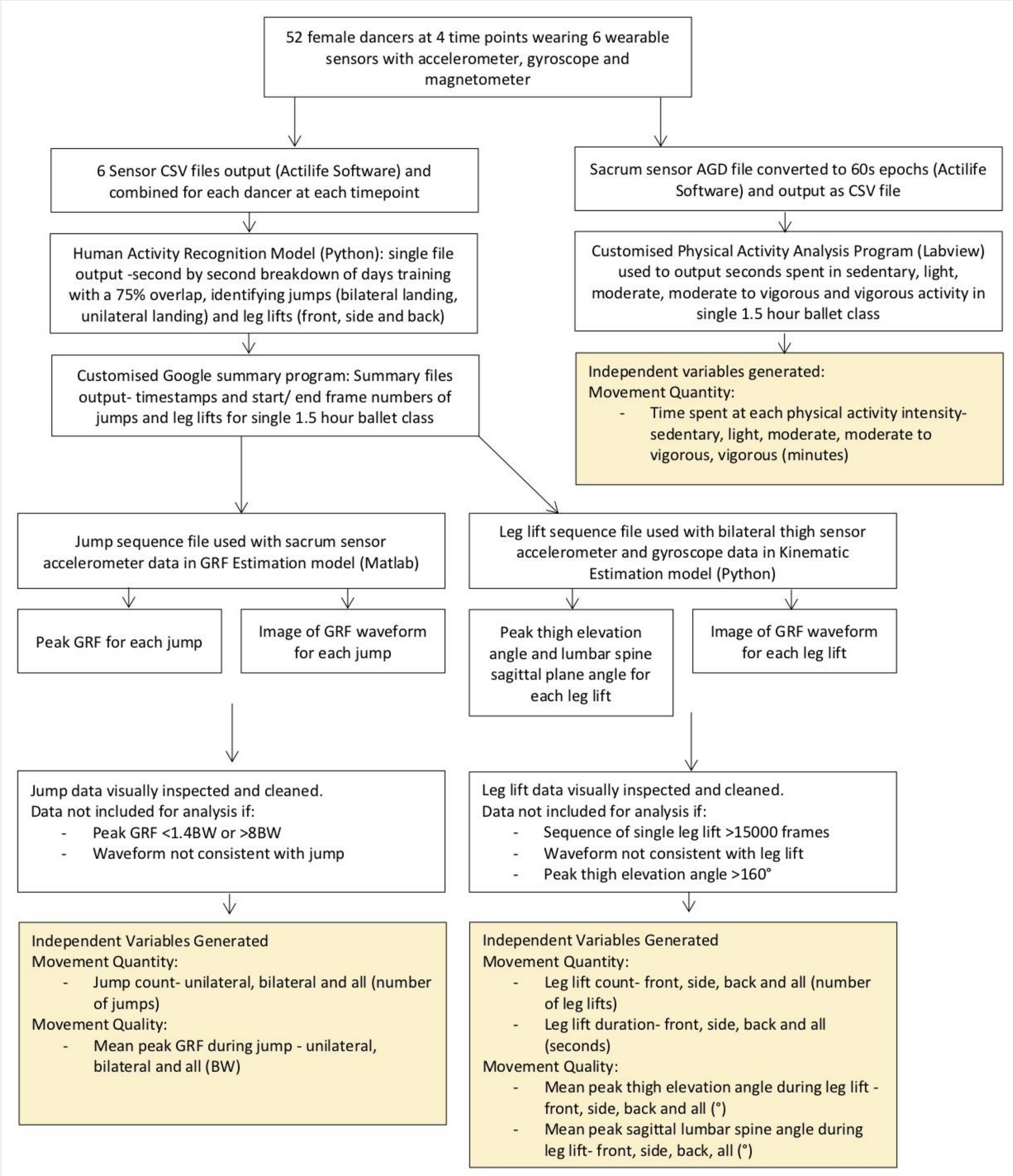
6.2.3.2 Movement quantity and quality

Dancers were fitted with a wearable sensor system consisting of 6 Actigraph GT9x Link (Actigraph, Pensocola, FL) wearable inertial measurement units, which include an accelerometer, gyroscope and magnetometer, operated at 100Hz, at previously detailed anatomical landmarks (thoracic spine, sacrum, bilateral thigh and bilateral shin) in order to estimate movement quantity and quality (Hendry et al., 2020a; Hendry et al., 2020b). Dancer's movement quantity was defined as the number of movements that a dancer performed or the time spent performing the movements, and movement quality was defined as the biomechanical characteristics of the movement. Specifically, the previously developed and validated system utilised machine learning models applied to raw data to estimate every occurrence of jumping (unilateral and bilateral jumps) and leg lifting (to the front, side and back), as measures of specific movement quantity (Hendry et al., 2020a). It then output peak GRF during jumps (with a potential error of 0.24BW for unilateral landings and 0.21BW for bilateral landings, as well as thigh elevation angles and lumbar spine sagittal angles during leg lift tasks (with a potential error of 6.8° and 5.7° respectively during leg lifts), as measures of movement quality (Hendry et al., 2020b; Hendry et al., 2021). In addition, the accelerometer data collected with the sacrum sensor was used to determine the physical activity intensity completed by the dancers using established physical activity intensity cut points (McVeigh et al., 2016), this was utilised as a measure of general movement quantity.

.Following data collection, the sensor data was processed and cleaned as described in the flow diagram in Figure 6.2. Extensive and comprehensive data cleaning was applied to remove any movements that were misclassified. Specific parameters applied for data cleaning are detailed in Figure 6.2. Initially, it was proposed that the dancers' quantity and quality of movement would be analysed over a full day of training. However due to the complex computational time we focussed on the best estimate of the dancer's load, which was their ballet class. Quantity and quality of movement within a single 1.5-hour ballet class at each time point was analysed.

General and specific quantity of movement variables were considered (Figure 6.2).

Figure 6.2
Flow diagram representing sensor data processing steps and variables generated



6.2.4 Statistical analyses

Sample demographics were summarised with descriptive statistics.

For aim 1, a series of linear mixed models were used to estimate the association between quantity and quality of movement and pain severity. Pain severity (NRS) was used as the dependent variable and, in separate models, quantity and quality of movement variables were used as the independent variable.

The level 1 unit of observation was occasion (4 measures over the semester), nested in participants as the level 2 unit of observation. For each model, within-person and between-person level associations were estimated separately using subject mean centering (Rabe-Hesketh & Skrondal, 2015). Between-person analysis seeks to explain how much the variability between the pain scores of different people is a function of differences in levels of movement between those people, whereas within-person analysis seeks to explain how much of the variability in pain a single person over time is a function of that person's levels of movement over time.

A likelihood ratio test was conducted to assess support for a random slope over a random intercept model, and nonlinear and linear effects for time were also evaluated. The association of year level (first, second or third year) and stream of dance (ballet or contemporary) with pain severity was assessed to evaluate the potential confounding of these variables on the between-person associations between pain severity and quantity and quality of movement variables. Regression coefficients with accompanying 95% confidence intervals and p-values are reported.

The same analyses were conducted for aim 2, using pain related disability (PSFS) as the dependent variable. All analyses were conducted using Stata/IC 16.0 for Windows (StataCorp LLC; College Station TX USA).

6.3 Results

Of the 52 dancers who consented to participate in this study, two dancers withdrew from the dance program after the second data collection period, and two more elected not to wear sensors for the final data collection due to skin irritation. These dancers were still included in the analysis, whereby the analysis model accounted for missing data. One dancer's data at all 4 time points was not usable as the human activity recognition machine learning model could not provide an output, and thus was excluded from analysis.

6.3.1 Participant characteristics

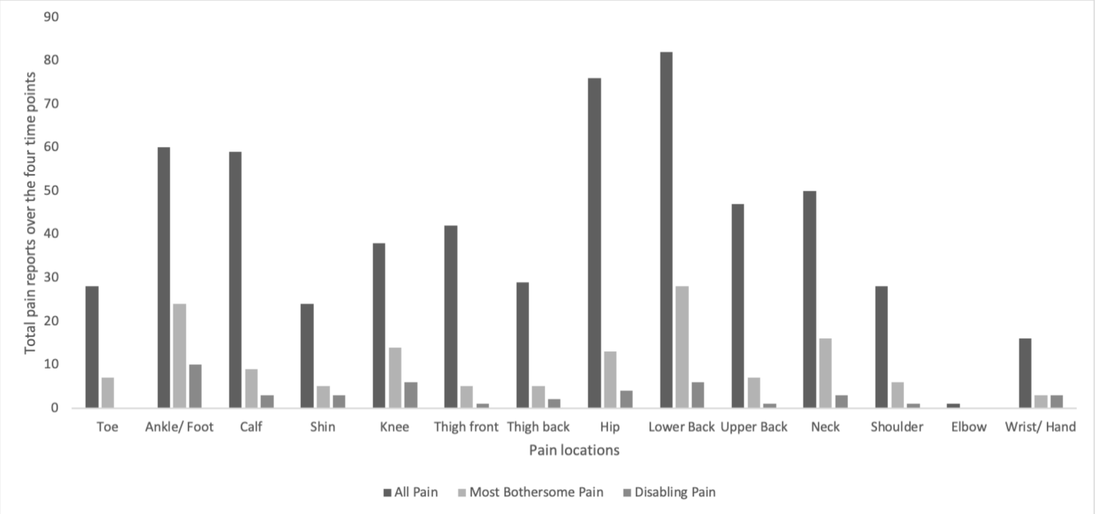
Participant characteristics are displayed in Table 6.1. There were similar numbers of ballet and contemporary focussed dancers represented in the sample, however there were more first-year dancers than second- and third-year dancers.

Table 6.1
Participant characteristics

Characteristic	Mean (SD)
Age (years)	18.4 (1.1)
Height (cm)	168.4 (5.4)
Weight (kg)	59.5 (5.8)
Years of dance training (years)	13.7 (3.0)
Year group (first/ second/ third)	26/16/10
Stream (ballet/ contemporary) (n)	28/ 24

Throughout the study, 50 of the 52 dancers experienced pain, and 26 of these reported PSFS scores of less than 7/10, classified as disabling pain. The frequency of reporting of all pain sites, most bothersome pain sites and disabling pain sites across all 4 time periods is demonstrated in Figure 6.3. When considering all pain presentations, the lower back was most commonly affected, followed by the hip and the foot and ankle. The lower back was most commonly nominated as the most bothersome, followed by the foot and ankle and 22 dancers reported multiple pain sites as most bothersome. The foot and ankle were most common area of disabling pain (< 7 on PSFS), followed multiple pain sites (9 presentations) and then the lower back. Only 2 of the dancers with disabling pain completely stopped dancing due to their pain. Both were due to acute traumatic injuries, the only two across the course of the study.

Figure 6.3
Frequency of pain reports by pain location



6.3.2 Relationship between movement quantity and quality with pain severity and pain related disability

The overall mean values for each variable at each time point are demonstrated in Table 6.2. Pain severity and pain related disability remained fairly constant over the 4 time points, and there was no statistical evidence for linear or non-linear effects for time for either outcome in linear mixed models (pain severity: coefficient -0.07, 95%CI: -0.32, 0.18, p=0.58, pain related disability: coefficient -0.10, 95%CI: -0.41, 0.22, p=0.55).

Of the large number of movement parameters examined, we identified only a small number of modest associations between dancers' movement quantity and quality and dancers' self-reported pain outcomes. In summary, there were no significant between-person level associations for pain severity, however increased pain related disability was associated with higher levels of light activity and a lower duration and count of leg lifts to the front and all leg lifts, and higher thigh elevation angles during side leg lifts. At a within-person level there were no significant findings for either pain severity or pain related disability. Results of the between-person and within-person analysis for movement quantity and quality are demonstrated in table form in Table 6.3.

When considering movement quantity, there was no evidence of between-person associations with pain severity after adjusting for year and stream.

When considering movement quantity, there was some evidence of between-person associations with pain related disability on adjusted analysis. very modest between-person associations with pain related disability on adjusted analysis. A 1-minute increase in light activity was associated with a reduction in patient specific functional scale of -0.15 points, 95%CI: -0.26, -0.03, p=0.02) equating to an association with increased pain-related disability. A 10 second increase in duration of front leg lifts was associated with a decrease in pain related disability of 0.19 points (95%CI: 0.04, 0.34, p=0.02).

Additionally, a 10-count increase in front leg lifts was associated with a decrease in pain related disability of 0.66 points (95%CI: 0.13, 1.19 p=0.02). Further, a 10-count increase in all leg lifts was associated with a decrease in pain related disability of 0.40 points (95%CI: 0.03, 0.76, p=0.03).

When considering movement quality, there was evidence of a between-person association with pain related disability on adjusted analysis, with a 10° increase in thigh elevation angle during side leg lifts was associated with an increase in pain related disability of 0.83 points. (95%CI: -1.57, -.0.09, p=0.03).

Table 6.2
Overall mean values for each variable at each time point

	Mean (SD) score at each time point			
	1	**2**	**3**	**4**
Pain				
Pain Related Disability (PSFS)	8.2 (2.7)	8.2 (3.0)	7.8 (3.3)	8.1 (2.9)
Pain Severity (NRS)	3.5 (2.1)	3.1 (2.1)	3.2 (2.3)	3.2 (2.3)
Movement Quantity				
General: Intensity				
Sedentary (mins)	29.5 (15.6)	29.7 (10.9)	25.6 (10.1)	21.8 (7.7)
Light (mins)	62.2 (8.9)	56.3 (7.2)	57.5 (7.5)	62.4 (11.0)
Moderate (mins)	7.5 (4.7)	11.8 (7.0)	13.4 (7.0)	9.6 (4.8)
Vigorous (mins)	1.4 (1.3)	2.4 (2.3)	1.8 (1.2)	2.9 (2.7)
Moderate to Vigorous (mins)	8.9 (5.3)	14.2 (8.4)	15.2 (7.4)	11.9 (6.3)
Specific: Leg lift				
Duration front (secs)	82.9 (64.5)	118.0 (71.1)	88.1 (56.3)	115.8 (68.3)
Duration side (secs)	28.3(29.1)	47.2 (31.6)	48.1 (30.7)	45.4 (34.8)
Duration back (secs)	36.6 (32.1)	70.9 (48.9)	82.1 (56.0)	68.5 (44.5)
Duration all (secs)	143.2 (96.7)	236.0 (108.9)	217.3 (106.3)	228.2 (105.5)
Count front	28.2 (20.8)	35.6 (16.2)	32.0 (19.0)	40.1 (21.7)
Count side	11.2 (9.0)	18.0 (11.6)	19.8 (11.0)	18.5 (15.1)
Count back	16.6 (15.9)	28.9 (15.1)	35.4 (23.2)	28.1 (19.4)
Count all	54.3 (35.9)	82.5 (27.7)	86.7 (39.6)	86.1 (40.7)
Specific: Jumps				
Count Unilateral	20.1 (21.7)	35.3 (27.9)	41.2 (33.6)	65.6 (67.9)
Count bilateral	7.9 (12.5)	19.6 (19.2)	20.0 (22.8)	28.1 (39.3)
Count all	25.7 (26.1)	53.4 (38.4)	59.4 (46.5)	90.7 (92.6)
Movement Quality				
Leg lifts				
Thigh elevation front (°)	93.7 (19.1)	91.9 (7.8)	90.3 (11.1)	84.4 (11.6)
Thigh elevation side (°)	110.9 (19.8)	104.6 (13.1)	110.9 (17.5)	102.6 (19.6)
Thigh elevation back (°)	91.2 (23.1)	84.2 (10.9)	84.5 (13.1)	80.3 (12.5)
Thigh elevation all (°)	96.7 (19.7)	91.6 (8.0)	91.9 (10.5)	86.8 (13.2)
Lumbar sagittal front (°)	-6.0 (4.34)	-6.7 (2.7)	-5.8 (3.4)	-4.7 (2.6)
Lumbar sagittal side (°)	-5.3 (4.9)	-4.9 (2.4)	-4.3 (2.5)	-3.8 (2.8)
Lumbar sagittal back (°)	29.4 (4.6)	29.9 (5.7)	30.4 (4.2)	31.7 (3.6)
Jumps				
GRF Unilateral (BW)	2.7 (0.4)	2.6 (0.3)	2.6 (0.3)	2.6 (0.4)
GRF Bilateral (BW)	2.7 (0.5)	2.8 (0.6)	2.6 (0.4)	2.7 (0.4)
GRF All (BW)	2.7 (0.4)	2.7 (0.3)	2.6 (0.3)	2.6 (0.3)

Secs: Seconds; Mins: Minutes; BW: Body weight; GRF: Ground reaction force

Table 6.3
Results of linear mixed models examining associations between quantity and quality of movement with pain severity and pain related disability

		Pain Severity Greater scores indicate greater pain severity				Pain Related Disability Lower scores indicate greater pain related disability			
		Unadjusted Analysis		Analysis adjusted for year and stream		Unadjusted Analysis		Analysis adjusted for year and stream	
		Coefficient (95% Confidence Interval)*	P	Coefficient (95% Confidence Interval)*	P	Coefficient (95% Confidence Interval)[#]	P	Coefficient (95% Confidence Interval)[#]	P
Movement Quantity: General									
Sedentary (mins)	Between	-0.04 (-0.08, 0.01)	0.07	-0.01 (-0.07, 0.04)	0.62	-0.02 (-0.08, 0.04)	0.46	-0.04 (-0.11, 0.04)	0.31
	Within	0.01 (-0.02, 0.04)	0.60			-0.01 (-0.06, 0.03)	0.50		
Light (mins)	Between	0.08 (-0.01, 0.17)	0.06	0.06 (-0.03, 0.14)	0.19	**-0.16 (-0.27, -0.05)**	**0.01**	**-0.15 (-0.26, -0.03)**	**0.02**
	Within	-0.01 (-0.04, 0.02)	0.43			0.01 (-0.03, 0.05)	0.63		
Moderate (mins)	Between	0.09 (-0.01, 0.18)	0.08	0.04 (-0.10, 0.17)	0.60	0.07 (-0.07, 0.20)	0.32	0.12 (-0.07, 0.31)	0.21
	Within	0.012 (-0.04, 0.07)	0.65			-0.01 (-0.78, 0.07)	0.88		
Vigorous (mins)	Between	**0.32 (0.02, 0.63)**	**0.04**	0.29 (-0.22, 0.79)	0.27	0.15 (-0.28, 0.58)	0.50	0.23 (-0.52, 0.98)	0.55
	Within	-0.09 (-0.25, 0.07)	0.27			0.00 (-0.22, 0.21)	0.98		
Moderate-Vigorous (mins)	Between	0.08 (0.00, 0.15)	0.05	0.05 (-0.07, 0.16)	0.44	0.05 (-0.060, 0.158)	0.38	0.09 (-0.08, 0.27)	0.29
	Within	0.00 (-0.05, 0.05)	0.96			0.00 (-0.068, 0.064)	0.96		

		Pain Severity Greater scores indicate greater pain severity				Pain Related Disability Lower scores indicate greater pain related disability			
		Unadjusted Analysis		**Analysis adjusted for year and stream**		**Unadjusted Analysis**		**Analysis adjusted for year and stream**	
		Coefficient (95% Confidence Interval)*	**P**	**Coefficient (95% Confidence Interval)***	**P**	**Coefficient (95% Confidence Interval)[#]**	**P**	**Coefficient (95% Confidence Interval)[#]**	**P**
Movement Quantity: Leg Lifts									
Duration front (secs)[a]	Between	0.01 (-0.11, 0.12)	0.94	-0.01 (-0.11, 0.11)	0.10	**0.18 (0.02, 0.32)**	**0.03**	**0.19 (0.04, 0.34)**	**0.02**
	Within	-0.01 (-0.05, 0.03)	0.67			0.001 (-0.04,0.07)	0.64		
Duration side (secs)[a]	Between	-0.11 (-0.12, 0.34)	0.37	-0.02 (-0.31, 0.27)	0.91	0.02 (-0.31, 0.35)	0.92	0.19 (-0.23, 0.63)	0.37
	Within	0.06 (-0.15, 0.03)	0.20			0.05 (-0.06, 0.17)	0.35		
Duration back (secs)[a]	Between	-0.02 (-0.17, 0.19)	0.87	-0.01 (-1.66, 0.19)	0.89	0.09 9 (-0.17, 0.36)	0.48	0.09 (-0.17, 0.36)	0.49
	Within	-0.01 (-0.07, 0.05)	0.70			0.02 (-0.05, 0.010)	0.54		
Duration all (secs)[a]	Between	0.02 (-0.05, 0.09)	0.58	0.01 (-0.06, 0.08)	0.82	0.08 (-0.02, 0.18)	0.13	0.10 (-0.01, 0.21)	0.06
	Within	-0.01 (-0.03, 0.02)	0.49			0.02 (-0.02, 0.05)	0.37		
Count front[b]	Between	0.14 (-0.21, 0.48)	0.44	-0.02 (-0.39, 0.34)	0.90	**0.51 (0.02, 0.99)**	**0.04**	**0.66 (0.13, 1.19)**	**0.02**
	Within	-0.03 (-0.19, 0.12)	0.66			0.08 (-0.11, 0.28)	0.39		
Count side[b]	Between	0.29 (-0.31, 0.89)	0.34	-0.30 (-0.18, 0.57)	0.50	0.13 (-0.73, 0.99)	0.77	0.85 (-0.45, 2.15)	0.12
	Within	-0.14 (-0.38, 0.09)	0.23			0.11 (-0.20, 0.42)	0.49		
Count back[b]	Between	0.24 (-0.15, 0.64)	0.24	0.10 (-0.34, 0.53)	0.67	0.16 (-0.42, 0.73)	0.59	0.19 (-0.46, 0.84)	0.56
	Within	-0.02 (-0.16, 0.13)	0.83			0.09 (-0.10, 0.27)	0.36		
Count all[b]	Between	0.13 (-0.06, 0.32)	0.17	0.01 (-0.24, 0.26)	0.93	0.18 (-0.09, 0.45)	0.18	**0.40 (0.03, 0.76)**	**0.03**
	Within	-0.02 (-0.10, 0.05)	0.55			0.06 (-0.04, 0.16)	0.23		

		Pain Severity Greater scores indicate greater pain severity				Pain Related Disability Lower scores indicate greater pain related disability			
		Unadjusted Analysis		Analysis adjusted for year and stream		Unadjusted Analysis		Analysis adjusted for year and stream	
		Coefficient (95% Confidence Interval)*	P	Coefficient (95% Confidence Interval)*	P	Coefficient (95% Confidence Interval)#	P	Coefficient (95% Confidence Interval)#	P
Movement Quantity: Jumps									
Count Jump unilateral[b]	Between	0.11 (-0.05, 0.27)	0.16	0.03 (-0.16, 0.23)	0.73	0.02 (-0.23, 0.26)	0.89	0.01 (-0.30, 0.32)	0.93
	Within	0.01 (-0.07, 0.09)	0.81			0.05 (-0.05, 0.14)	0.34		
Count Jump bilateral[b]	Between	0.13 (-0.20, 0.46)	0.43	0.07 (-0.31, 0.45)	0.71	-0.11 (-0.63, 0.40)	0.66	-0.24 (-0.86, 0.37)	0.44
	Within	0.12 (-0.01, 0.25)	0.07			0.01 (-0.15, 0.16)	0.94		
Count Jump all[b]	Between	0.08 (-0.04, 0.20)	0.19	0.03 (-0.12, 0.18)	0.71	-0.03 (-0.21, 0.16)	0.78	-0.06 (-0.30, 0.18)	0.61
	Within	0.03 (-0.02, 0.09)	0.25			0.03 (-0.04, 0.10)	0.38		
Movement Quality: Leg Lifts									
Thigh elevation all (°)[c]	Between	0.14 (-0.75, 0.47)	0.64	-0.05 (-0.79, 0.70)	0.90	-0.31 (-1.18, 0.56)	0.48	-0.08 (-1.21, 1.05)	0.89
	Within	-0.04 (-0.18,0.25)	0.74			-0.12 (-0.39, 0.16)	0.41		
Thigh elevation front (°)[c]	Between	-0.40 (-1.01, 0.20)	0.19	-0.47 (1.17, 0.22)	0.18	0.05 (-0.94, 0.83)	0.91	0.29 (-0.77, 1.36)	0.59
	Within	0.03 (-0.18, 0.23)	0.80			-0.04 (-0.31, 0.23)	0.75		
Thigh elevation side (°)[c]	Between	0.25 (-0.27, 0.72)	0.31	0.31 (-0.20, 0.82)	0.23	**-0.83 (-1.47, -0.19)**	**0.01**	**-0.83 (-1.57, -0.09)**	**0.03**
	Within	0.05 (-0.11, 0.20)	0.54			-0.08 (-0.28, 0.12)	0.45		
Thigh elevation back (°)[a]	Between	0.18 (-0.29, 0.65)	0.46	0.33 (-0.16, 0.82)	0.18	--0.57 (-1.22, 0.08)	0.09	-0.56 (-1.30, 0.18)	0.14
	Within	0.06 (-0.12, 0.24)	0.51			0.10 (-0.33, 0.13)	0.40		

		Pain Severity Greater scores indicate greater pain severity				Pain Related Disability Lower scores indicate greater pain related disability			
		Unadjusted Analysis		Analysis adjusted for year and stream		Unadjusted Analysis		Analysis adjusted for year and stream	
		Coefficient (95% Confidence Interval)*	**P**	**Coefficient (95% Confidence Interval)***	**P**	**Coefficient (95% Confidence Interval)#**	**P**	**Coefficient (95% Confidence Interval)#**	**P**
Lumbar sagittal front (°)[c]	Between	0.12 (-1.88, 2.13)	0.91	0.41 (-1.58, 0.241)	0.69	-1.88 (-4.75, 0.98)	0.19	-2.66 (-5.61, 0.30)	0.08
	Within	0.04 (-0.83, 0.92)	0.92			0.40 (-0.74, 1.53)	0.49		
Lumbar sagittal side (°)[c]	Between	0.67 (-2.29, 3.64)	0.66	0.48 (-2.57, 3.53)	0.76	-2.30 (6.60, 2.00)	0.29	-3.77 (-8.36, 0.81)	0.10
	Within	-0.23 (-1.06, 0.59)	0.58			-0.25 (-1.31, 0.82)	0.65		
Lumbar sagittal back (°)[c]	Between	-1.16 (-3.00, 0.68)	0.22	-0.69 (-2.53, 1.15)	0.46	-0.41 (-3.07, 2.25)	0.76	-0.50 (-3.23, 2.32)	0.75
	Within	-0.18 (-0.79, 0.43)	0.56			-0.011 (-0.91, 0.69)	0.79		
Movement Quality: Jumps									
GRF unilateral (BW)	Between	1.48 (-0.44, 3.40)	0.13	0.72 (-1.50, 2.94)	0.52	1.12 (-1.56, 3.80)	0.41	1.73 (-1.46, 4.93)	0.29
	Within	-1.01 (-2.10, 0.08)	0.07			-0.29 (-1.70,1.13)	0.69		
GRF bilateral (BW)	Between	0.61 (-0.79,2.01)	0.39	0.49 (-0.95, 1.92)	0.51	-0.31 (-2.30, 1.67)	0.76	-0.65 (-2.75, 1.45)	0.55
	Within	0.75 (-0.86, 2.35)	0.36			-0.23 (-1.10, 0.64)	0.61		
GRF All (BW)	Between	1.44 (-0.42, 3.31)	0.13	1.10 (-0.84, 3.04)	0.27	0.27 (-2.30, 2.84)	0.84	-0.01 (-2.76, 2.74)	1.00
	Within	-0.99 (-2.05, 0.07)	0.07			-0.01 (-1.37, 1.34)	0.99		

Secs: seconds; Mins: minutes; BW: Body weight; GRF: Ground reaction force
a Coefficients represent the change in y for a 10s change in duration of leg lifts
b Coefficients represent the change in y for a 10 repetitions of movement
c Coefficients represent the change in Y for a 10° increase in angle
*Positive signed coefficient indicated increase in the independent variable associated with increased pain severity
#Negatively signed coefficient indicated increase in the independent variable associated with increase in pain related disability

6.4 Discussion

This field-based study utilised wearable sensor technology combined with machine learning methods to repeatedly monitor the movement quantity and quality for 52 dancers during their ballet classes over 4 time periods, in the lead up to and following a performance in a 12-week university semester. Some associations between self-reported pain outcomes with field-based movement quantity and quality were identified at the between-person level. While there was no evidence of associations with dancers self-reported pain severity, a few modest associations were identified between some movement factors and pain related disability. There was no evidence of changes over the 4-time points time in either pain or pain related disability. The methods used in this study provides a platform for further longitudinal research using continuous dancer monitoring to understand the complexities related to the development of, and responses to pain and pain related disability in dancers.

There was a high prevalence of musculoskeletal pain reported within this sample of dancers, with almost all dancers (50 out of 52) reporting having musculoskeletal pain at some point during the semester. The foot and ankle, and lower back were the sites most commonly reported for presence of pain, most bothersome pain and disabling pain. These findings are consistent with previous literature, where a systematic review has demonstrated a 14-57% prevalence for foot and ankle pain and 62% for low back pain (P. J. Smith et al., 2015). Further, the prevalence of disabling pain was lower, with half the dancers reporting disabling pain at some point during the semester. This is consistent with previous work, where the prevalence of dance related pain is influenced by how it is defined (Kenny et al., 2016). In our cohort, while half of the dancers experienced disabling pain across the semester, only two ceased dancing completely for at least 1 day due to their pain. The rest persisted, with some training modifications, which may reflect relatively low levels of pain and disability. Alternatively, it may reflect a culture of persisting in dance activities regardless of pain (Anderson & Hanrahan, 2008; Encarnacion, Meyers, Ruan, & Pease, 2000), or that movement is only modestly associated with pain.

Interestingly, there was no evidence for associations between pain severity and both movement quantity and quality when year and stream were accounted for. This result suggests that irrespective of pain intensity, dancers continue to engage in a similar amount of training and with the same movement quality.

Considering pain related disability, there was evidence for some weak between person associations for movement quantity. At a between-person level, greater levels of disability were associated with larger amounts of time spent in light intensity activity. Additionally, greater levels of disability were associated with a lower leg lift count to the front and overall, as well as less time spent performing leg lifts to the front. It is widely cited that dancers frequently continue to dance despite the presence of pain and related disability (Anderson & Hanrahan, 2008; Encarnacion et al., 2000). The results of our research suggest that while dancers continue to dance when experiencing pain, they do so with small modifications of movement quantity. It is possible that these findings reflect an adaptive response to reduce load, while continuing to dance with disabling pain. An alternative hypothesis is that the observed reduction in load is indicative of dancers' lack of strength, which may in turn lead to increased pain related disability. Further research involving daily dancer monitoring and temporal analysis would provide indication of causality and the bidirectional relationship of movement and pain.

There was also evidence for some weak associations between pain related disability and movement quality, specifically, greater pain related disability was associated with greater thigh elevation angles during side leg lifts. Initially this came as a surprise as movement is thought to be more constrained in the presence of pain and disability (Bauer et al., 2017), however a systematic review has identified that when experiencing disabling pain, people move with greater movement variability (Baida, Gore, Franklyn-Miller, & Moran, 2018). Considering these findings together, it could be hypothesised that dancers with higher levels of disability were modifying their training behaviours in some ways to reduce general load (e.g., reducing the volume of movement), while also modifying behaviours in ways which may increase specific joint loading (e.g., pushing how high they lifted their leg during side leg lifts). However, it cannot be assumed that all dancers were employing these strategies. Indeed, the low number of differences in movement, and with no clear pattern, may suggest that dancers are generally able to maintain movement quality despite pain. Additionally, analysis did not account for the specific movements that dancers reported as provocative. Thus, moving forwards in unravelling the individual complexity of the relationship between movement quality and quantity and pain, it may be more helpful to evaluate these associations, using serial monitoring of individual dancers rather than investigating group differences.

Interestingly, there was no evidence for an association between either pain severity or pain related disability and any jumping variables, suggesting that the dancers may be able to maintain movement quantity and quality irrespective of pain, during jumping activity. This finding challenges findings of a previous cross-sectional study comparing dancers with and without anterior knee pain (n=25) suggested that those with pain demonstrated greater peak GRF during a ballet specific jump (mean difference 0.2BW, CI: 0.08, 0.32) (Peng et al., 2015). However, this study was limited in that it only captured a single trial of a jump on a single day, and only considered pain presence rather than pain severity. In contrast, we captured all jumps within the dancers' daily class at 4 different time points, taking into consideration changes in pain severity at each of these time points. Another explanation may relate to the relatively low levels of pain observed in this study, with average pain scores ranging from 3.1-3.5/10 across the 4 time points. It is possible that the threshold for marked changes in movement in response to pain was not met, in line with previous experimental research (Henriksen, Rosager, Aaboe, Graven-Nielsen, & Bliddal, 2011). Finally, pain location may also influence these findings, where it can be hypothesised that a dancer with foot, ankle or knee pain may land differently to a dancer with hip or low back pain. With serial monitoring of individual dancers in future research, the relationship between movement quality variables specific pain locations and the changes in pain severity relative to these locations may be explored.

6.5 Strengths and limitations

Previous research in this space has focussed predominantly on general movement quantity with limited focus on specific movement quantity and movement quality. Thus, a major strength of this study is the unique combination of movement quantity and quality measures and the exploration of their relationship with pain and disability. Importantly, this study used technology that allowed for field-based measurement of movement in a dancer's normal ballet class environment. This system was able to detect common ballet movements that are considered potentially pain provocative. The serial design allowed for observation at the within-person level, however the use of only 4 time points was a limitation as discussed below.

The study was limited to a sample of pre-professional female dancers from a single dance training facility. To promote generalisability, future research should include dancers from multiple centres and include male and non-binary dancers as variations in training regimes across facilities, and gender specific movement profiles may influence results.

For example, the greater volume of jumping activities performed by male dancers, could mean jumps are more strongly associated with pain and / or disability in men.

The fact that we only identified evidence for between-person associations may be a result of the study design. Repeated measures at only 4 time points over a 12-week period rather than daily monitoring, reduced the information available to elucidate associations at the level of the individual dancer. Furthermore, the variation in pain location, and task selection for the PSFS, over the 4 time points both within dancers across time, as well as between dancers, was not possible to account for within the analysis with the numbers available. The study also only considered physical factors associated with pain and disability, when pain is known to be a complicated biopsychosocial construct (Hainline, Turner, Caneiro, Stewart, & Moseley, 2017). This study is proof-of-concept that the field-based system used could allow future research to evaluate these associations at an individual level using serial monitoring over time. This would provide adequate data for sophisticated temporal analyses to further unravel the complexities of dancers' pain and disability.

To our knowledge this is the first application of machine learning to wearable sensor data that has been used in a longitudinal field-based study. However, a number of challenges of the wearable sensor system need to be addressed before more sophisticated applications of the wearable sensor system can be undertaken. The system required multiple sensors being attached to each dancer and, as detailed in Figure 6.2, there were several steps in the processing of data due to multiple machine learning models which, combined with the computational demands of the machine learning algorithms, resulted in lengthy data processing. Additionally, while the human activity recognition model used demonstrated an acceptable degree of accuracy when validated in previous work (Hendry et al., 2020a), the application of this system in a true field-based study required extensive manual data cleaning as the accuracy of classification varied amongst the dancers. Specifically, each identified movement was visually inspected by 1 of the researchers and removed if the movement was misclassified. This was why only a single dance class was analysed on each of the 4 days. All previous applications have focused on the development and validation of systems, thus have not accounted the extensive data processing and cleaning that is required when these novel models are applied in field-based settings (Chambers et al., 2015). To allow for larger studies with continuous daily monitoring the machine learning models would require further optimisation, to allow for a fully automated accurate system.

6.6 Clinical implications and conclusions

The results of this study provide insight into how dancers with disabling pain may adapt the way they move to reduce load, in order to continue dancing. However, it is unlikely that these same responses are adopted by all dancers when faced with pain and pain related disability. Further, it is likely that complex interactions between movement quantity and quality, as well as other biopsychosocial factors, that are unique to each individual, influence a person's pain development and coping responses to pain. Future application of wearable sensor technology provides the opportunity for clinicians to gain a deeper insight into the inter-relationships between pain, disability, and movement in athletic populations, to better inform person centred care.

The field-based sensor system used in this research can provide quantitative information on both movement quantity and quality in a real-world environment. While further optimisation of the technology used in this research is needed to promote ease of usability, this research demonstrates a proof-of-concept for larger, longitudinal field-based research to occur. Specifically, it provides future opportunity using frequent, field-based, serial measures of movement quantity and quality in a dancer's everyday training, to allow the collection of the large amount of data needed for modelling the complexity of interrelationships between movement, pain, disability and other salient factors, using sophisticated analytics such as complex systems approaches (Bittencourt et al., 2016). This creates opportunities within clinical research and practice for assessment and monitoring of individual dancers, and detect shifts in individual dancer movement behaviours in response to treatment or advice.

Chapter Seven

7

Discussion and Conclusions

The main aims of this thesis were: to (i) develop and validate a field-based system capable of capturing field-based measures of dance-specific movement quantity and quality, and (ii) to determine if there was a relationship of dancers/ movement quantity and quality with self-reported pain and pain related disability outcomes across a 12-week period.

This chapter integrates the main findings of this thesis, detailing the evolution of monitoring dancers' movement quantity and quality, providing a proof-of-concept to assist in unravelling the complexities of dancers' pain and pain related disability. After summarising the findings of the studies conducted for this thesis, this chapter will discuss the measurement of dancers' movement quantity and quality and understanding of the associations with dancers' pain and pain related disability. Specific focus will be brought to where the field begun prior to this work, how the field has progressed during the thesis work, including how this thesis has advanced the field, and finally opportunities for future research and clinical applications. The chapter will conclude by summarising the limitations of the thesis and providing further recommendations for future research before final remarks are made.

7.1 Summary of the thesis developments and findings

In the first 2 studies of this project, presented in Chapters 3-5, a field-based wearable sensor system which was capable of measuring dancers' movement quantity and quality was developed and validated. This system consisted of a series of machine learning models applied to wearable sensor data.

The first study, presented in Chapter 3, focussed on the development of a human activity recognition system, using convolutional neural networks for the measurement of dance-specific movement quantity. Specifically, the study aimed to develop a system capable of the detection of dance-specific jumping and leg lifting tasks. The jumps and leg lifts were classified at 3 different levels. The primary aim of the study was to develop and validate the human activity recognition system. The study also investigated if the degree of accuracy changed at each level of movement classification and with different sensor numbers and locations. Finally, whether the inclusion of transitions influenced accuracy was explored. Machine learning models were developed using convolutional neural networks for every combination of 6 sensors (6,5,4,3,2 etc). With the inclusion of data from all 6 sensors and without transitions the model performed with 97.8% accuracy. As expected, the degree of accuracy reduced at the second and third level of classification and also when transitions were included, number of sensors were reduced and with different sensor combinations. The main outcomes of this study were two-fold. Firstly, the system developed allows for the objective quantification of specific training volumes as a measure of movement quantity in dancers. Secondly, capturing jumping and leg lifting tasks from a string of wearable sensor data allows for analysis of dancers' movement quality during these movements.

The second study, presented in Chapters 4 and 5, focussed on the development of a series of machine learning models for the estimation of ground reaction force (GRF) during jumping tasks (Study 2A), and thigh elevation angles and lumbar spine sagittal angles during leg lifting tasks (Study 2B). Study 2A, presented in Chapter 4, detailed the multi-stage development and validation of machine learning models, applied to wearable sensor data, for the estimation of GRF during dance-specific bilateral and unilateral jumps. In the first stage of model development, where models were initially trained and tested on a sample of 14 dancers, the best performing single sensor model was determined and this was the sacrum sensor. During the second stage of model development, when the sacrum sensor model was optimised and trained and tested further on 23 dancers the average RMSE was 0.42BW for the unilateral models and 0.39BW for the bilateral models. Study 2B, presented in Chapter 5, detailed the multi-stage development and validation of machine learning models, applied to wearable sensor data, for the estimation of thigh elevation and lumbar sagittal angles during dance-specific leg lifting tasks. In the first stage of model development, the best performing model was the bilateral thigh sensor model. In the second stage of development, when this model was refined and optimised, the average RMSE for thigh elevation angle across the complete leg lift profile was 6.8° and for lumbar spine sagittal plane angle the RMSE was 5.6°, with strong correlation between the machine learning and gold standard optical motion capture systems.

In Study 3, presented in Chapter 6, the machine learning models developed in the first 2 studies were applied within a longitudinal field-based investigation that aimed to determine the association of dancers' movement quantity and quality with pain severity and pain related disability. Fifty-two dancers were monitored over a 12-week period, in the lead up to and following a performance. On 4 separate days, dancers wore the wearable sensors and completed a series of questionnaires about their pain and disability. Movement quantity and quality data from their ballet class was extracted from the wearable sensor data using the machine learning models. Overall, dancers reported low levels of pain severity and disability, and results of the mixed methods analysis demonstrated evidence of group level associations for some movement parameters and pain related disability. There were no associations evident for pain severity. This proof-of-concept research provides a compelling model for future work exploring dancers' pain using field-based, serial data collection.

7.2 Measuring movement quantity and quality in dance

7.2.1 Past and current methodologies: What other work in this field has demonstrated

Prior to the inception of this thesis in January 2017, while several researchers had suggested that the high training volumes that dancers partake in may be associated with pain and pain related disability, no publications had formally evaluated this relationship. However, during the course of this PhD there have been 7 new publications exploring the relationship of training loads with pain and pain related disability in dancers in the last 4 years (Boeding et al., 2019; Cahalan et al., 2019; Cahalan, Kearney, et al., 2018; Jeffries et al., 2020; L. Lee et al., 2017; Shaw et al., 2021; Volkova & Kenny, 2020). These studies are summarised in Table 2.1, within the literature review in Chapter 2. Within this body of literature dancers' training volumes have generally been measured as dancers' general movement quantity, and all of the studies utilised subjective and schedule-based reporting. Specifically, researchers have utilised dancers' self-reported training hours per week (Cahalan, Bargary, et al., 2018; Cahalan et al., 2019; Volkova & Kenny, 2020), their training and performance schedules (L. Lee et al., 2017; Shaw et al., 2021), and their "session rating of perceived exertion" ("session RPE") (Boeding et al., 2019; Jeffries et al., 2020), which is the product of the duration of dance activity session (based off schedules or self-report) and the dancers' perceived activity intensity.

While these methods provide an overall sense of how much a dancer trains and moves within their day, as well as their perception of effort they come with certain limitations. Self-reporting of training loads has recently been challenged as athletes have reported feeling burdened by having to self-report data (Murphy et al., 2021; Saw, Main, & Gastin, 2015) In an effort to optimise athlete mental health, it has been suggested that non-essential stressors and burdens, such as reporting of training loads, are minimised (Murphy et al., 2021). Self-reported training hours are also highly subjective and prone to bias (Murphy et al., 2021), where dancers may overestimate or underestimate the number of hours that they have trained and performed. Further, while schedules reflect the number of programmed or planned hours of training, neither schedules nor self-report, clearly capture the specific movements that a dancer performs within their training (Shaw et al., 2021). The perception of effort captured within "session RPE" is useful may provide some indication of how a dancer feels following a training session, thus could be indicative of the overall burden of training on a dancer, however it does not capture the specific movements they have performed and the loads that these movements have imposed on their body. Based on choreographic demands and individual dancer goals, the specific movements performed may be highly variable both between and within dancers (Liederbach et al., 2006; Wyon et al., 2011). For example, if a dancer is preparing for a role requiring a high volume of jumping activity, she may increase the number of jumps she is performing within class and rehearsal. She may perform more jumps than another dancer with a similar schedule, and perform more jumps than she would if she were training towards a different role or working on a different goal.

The use of wearable sensor technology to capture dancers' training volume, while mainstream in some elite sports, is only emerging within the field of dance. As summarised in Chapter 2, physical activity intensity, using metabolic cut points has been captured in professional ballet dancers (Kozai et al., 2020), and movement quantity has also been captured in professional contemporary dancers using vector magnitude (Jeffries et al., 2016). These measures capture overall movement quantity however do not provide indication of either specific movement quantity.

While several of these recent longitudinal studies have explored the relationship of dancers' movement quantity and pain, no publications were identified which longitudinally explored the relationship between dancers' movement quality and pain or pain related disability. Historically, the relationship between dancers' movement quality and pain has been primarily captured within cross-sectional studies using laboratory-based measurement systems (Fietzer et al., 2012; H.-H. Lee et al., 2012; Peng et al., 2015). The gold standard measurement tools are force platforms and 3-dimensional optic motion capture systems for GRFs and range of movement respectively. However, these large systems are expensive and require the dancer to leave their normal training environment for measurement, thus have limited ecological validity and are not appropriate for serial measurements.

7.2.2 The present: What this thesis adds to the field

7.2.2.1 Development of a system using machine learning applied to wearable sensor data for the measurement of movement quantity and quality in dance

The first 3 results chapters of this thesis, together demonstrate for the first time, the application of 6 wearable sensors and 3 machine learning systems, combined as a single system, to objectively measure dancers' movement quantity and quality with acceptable validity, during dancers' normal training. Specifically, with acceptable accuracy it is possible to output: 1) the number of jumps and leg lifts and when they occur, and 2) the GRF during jumping and the thigh elevation and lumbar spine sagittal angles during leg lifting.

7.2.2.2 Determining which models to use within the field-based study: A balance between accuracy and practicality

Within Study 1 4416 machine learning models were required to be developed in order to assess every possible combination of the 6-sensor location, (64 possible combinations), at each of the 3 levels of classification, and validate them using a leave-one-out cross validation process (23 participants). Thus, a process to determine which of this large volume of models would be used within the final field-based study was undertaken. This decision-making process required a careful balance of subjective and objective factors.

Subjectively, concepts such as practicality of the system and level of detailed information was considered. The objective considerations were the accuracy of the system. This balance between practicality and accuracy allowed the optimal system to be adopted for the final field-based data collection.

The results of Study 1 indicated that the highest degree of accuracy (97.8%) would be achieved using all 6 sensors, without the inclusion of transitions and at the first level of classification, whereby the model was able to determine if the dancer was jumping or lifting her leg. This degree of accuracy is similar to what has been reported in several other human activity recognition studies for a range of athletic tasks (Cust et al., 2019). The level of accuracy for all published studies identified are demonstrated in Table 2.3 and Table 2.4. Table 2.3 demonstrates findings from publications prior to the commencement of machine learning model development and Table 2.4 demonstrates findings in publications since the commencement of model development.

However, the machine learning system that yielded the highest degree of accuracy, was not deemed suitable for application in our field-based study, due to the lack of specificity of task demands at the first level of classification, the omission of transitions in this model and the use of multiple sensors. These reasons are described further below. Therefore, a trade-off of accuracy for practicality in real-world use was required.

7.2.2.3 Levels of classification

With each level of classification the amount of detail of the movement increased, however the degree of accuracy of the system decreased. The first level of classification simply quantified when and how often a dancer jumped or lifted their leg, with no indication of the type of jump or direction of leg lift. The second level however, provided further detailed insight on the type of jump (bilateral, unilateral or large) and direction of leg lift and the third level provided indication of laterality.

The first level of classification detailed whether dancers were jumping or lifting their leg, not taking into consideration the specific type of jump or leg lift. Within their training and performance, dancers perform a range of different jumping and leg lifting tasks and the movement quality and in turn physical loading during these vary with task demands. Ground reaction forces during jumping varies dependent on the type of jump a dancer performs. Further the thigh and lumbar kinematics demonstrated during leg lifts to the back are very different to those demonstrated during a leg lift to the front or side (Bronner, 2012; Bronner & Ojofeitimi, 2011; Charbonnier et al., 2011). Previous laboratory-based studies have demonstrated that leg lifts to the back are characterised by substantial hip and lumbar spine extension, whereas front and side leg lifts are characterised by hip flexion and the lumbar spine has much smaller amounts of movement (Bronner, 2012; Bronner & Ojofeitimi, 2011; Mira et al., 2019). The differences in physical loading in these variations of jumping and leg lifting activities highlight the need for a system that is able to detect more than whether a dancer is simply jumping or lifting their leg.

Models developed at the second level of classification were able to determine if the dancer was performing a small bilateral jump, small unilateral jump, or large jump (which typically also land unilaterally). A 6 sensor model at the second level of classification without transitions performed with a degree of accuracy of 83%. These results were consistent with previous findings in tennis and Australian Rules Football, where the degree of accuracy of a system for detecting different tennis strokes reduced with increasing complex classifications of the tennis strokes (97.4% accuracy at the first level of classification and 93.2% at the second level in tennis and 83% accuracy at the first level of classification and 80% at the second level in Australian Rules football) (Cust et al., 2021; Whiteside et al., 2017). The third level of classification in the current study provided indication of laterality for single limb jumps and leg lifts, however accuracy was further reduced at this third level to a level deemed insufficient. Thus, the models developed at the second level of classification were deemed to most appropriately balance detailed information with accuracy.

7.2.2.4 Transitions

Model performance also reduced with the inclusion of transitions. Transition movement was anything that was not a jump or a leg lift task. These are important as in dance movement is rarely performed discretely. Rather, it is influenced by the movements that proceed and follow it, thus a model that can differentiate transitions from movmeents of interest is more ecologically valid than one without. When transitions were included, the 6 sensor model at the second level of classification performed with a degree of accuracy of 77.1%.

Prior to the commencement of this research, in our review of the literature (Chapter 2) there appeared to be only 1 other study that had utilised transitions in the development of their machine learning models (Schuldhaus et al., 2015). A human activity recognition model for the detection of kicks in soccer was developed using data from two shoe-attached wearable sensors worn by 23 soccer players (Schuldhaus et al., 2015). The machine learning models were trained and tested using data from 11 of the players, where each movement was classified as a pass, shot or "other" (i.e. a transition) (Schuldhaus et al., 2015). Leave-one-out cross validation yielded a degree of accuracy of 88.6% for detecting the different shots and 96.7% for detecting anything that was a transition (Schuldhaus et al., 2015). However when the model was validated in a real-world soccer match, the accuracy of the model reduced (84.2% for detecting different shots and 89.2% for detecting transitions in the real-world setting) despite the inclusion of transitions (Schuldhaus et al., 2015). Match-play model performance of 84.2% for detecting different shots, exceeds the match-play model performance of a manufacturer developed model for the detection tackles in Australian Rules Football, which detected only 18% of tackles within a game (Gastin et al., 2014). It was unclear whether the manufacturer developed model used in the Australian Rules Football study included transitions. Eighteen percent accuracy is also lower than the degree of accuracy achieved at any level of classification and with any combination of sensors with the inclusion of transitions demonstrated in this thesis. This difference in accuracy supports the notion that the inclusion of transitions may provide superior real-world performance. As a result, the lower degree of accuracy demonstrated by the 6 sensors model, at the second level of classification, with transitions, was chosen for use in Study 3 as it would potentially promote better real-world performance of the system within our field-based study.

7.2.2.5 Number of sensors

A system which required a minimum number of sensors would be ideal for field-based use in dance. The results of Study 1 indicated that the degree of accuracy reduced as the number of sensors reduced. Therefore, given the compromises in accuracy that were made to accommodate for level of classification and transitions, it was decided that the full 6 sensor set would provide the most accurate results for both movement quantity and quality in the longitudinal field-based study.

Interestingly, while the full 6 sensor model was deemed to have the highest degree of accuracy for the human activity recognition model, for the models developed for estimation of movement quality variables, the use of fewer sensors yielded higher accuracy. For both the unilateral and bilateral jumping GRF estimation models, the degree of accuracy was very similar whether we utilised multiple sensors or the single sacrum sensor, with a RMSE of 0.25BW for both the single sacrum sensor and 6 sensor unilateral landing models. The bilateral landing single sacrum sensor and 6 sensor models also had similar degrees of accuracy (RMSE= 0.24 and 0.21BW respectively). Interestingly, when the single sensor model was trained and tested on more dancers, the accuracy reduced. The reduction in accuracy may have been due to an imbalanced data set, resulting in overfitting, as described in Chapter 4, page 74. The model that performed with the greatest degree of accuracy for the estimation of hip and lumbar angles was the model using the sensors from both thighs (bilateral thigh model), using only 2 sensors, with an RMSE of 6.8° for thigh elevation angles and 5.6° for lumbar spine sagittal plane angles. Of note, the 6 sensor model was not identified as one of the top 10 performing models, and all of the top 10 performing models used data from 2, 3 or 4 sensors.

The models developed for estimation of movement quality variables performed with a comparable accuracy to other applications of machine learning to wearable sensor data for estimation of GRF and joint angles in running. Wouda et al (2018) demonstrated 2 artificial neural networks that were capable of estimation of GRF and knee sagittal joint angles during the cyclical task of running, using 3 wearable sensors (bilateral shin and sacrum). The models demonstrated an RMSE 0.39BW for GRF and 9.3° for sagittal knee joint angles in running, both greater than the error demonstrated in the current study. Other publications in this area have reported substantial differences between single sensor and multisensor models. Specifically, a 15.9% difference in the RMSE of a single sensor (RMSE = 29.7%) and multisensor (RMSE = 13.9%) convolutional neural network model, was reported (Johnson et al., 2019; Johnson et al., 2021). Conversely, a single sacrum worn sensor model developed on 37 running athletes performed with a lower RMSE of 0.15BW. It is possible that the greater degree of accuracy in the latter study was due to the larger sample size used for model training (Alcantara et al., 2021). For the estimation of joint angles, all published research identified utilised multisensor models, combining between 3 and 14 sensors for bilateral joint angle estimation (Argent et al., 2019; Dorschky et al., 2020; Mundt et al., 2020; Wouda et al., 2018). While the degree of accuracy reported in this thesis was similar, the model had the added advantage of estimating GRF during varied dance tasks than the cyclical task of running.

7.2.3 The final system

Based on the process detailed above where concepts around practicality and information required were weighed up against accuracy, it was decided that the 6-sensor system, at the second level of classification, with the inclusion of transitions would be the optimal model for our field-based study. The 77.1% level of accuracy was deemed sufficient and superior to previously used subjective and schedule-based measures for movement quantity (Phibbs et al., 2017). Additionally, the performance of this model compares favourably to a manufacturer developed commercially available model and sensor, called VERT (Benson et al., 2020; Charlton et al., 2017; Skazalski, Whiteley, Hansen, & Bahr, 2018). VERT is a wearable sensor programmed for automated jump detection in athletes. While the manufacturer's website claims that the system is utilised by over 350 sporting teams at elite and professional levels, peer review publications validating the system exist only in basketball and volleyball (Benson et al., 2020; Charlton et al., 2017; Skazalski et al., 2018). When applied to 46 basketballers, the VERT was able to accurately identify only 68% of all jumps within a basketball game (Benson et al., 2020). However when considering the jump height threshold of 15cm that the algorithm was programmed with, 91% of jumps that were over this threshold were detected (Benson et al., 2020). When worn by volleyballers, the VERT was able to accurately detect 89-99% of all jumps (Charlton et al., 2017; Skazalski et al., 2018). The VERT also estimates GRF, however no peer reviewed publications were identified where this feature was validated. While the accuracy of the VERT is higher than the accuracy in the final model of the current study, the VERT has not been applied to and validated in dancers. Additionally, it can only detect jumps, and no other tasks, and does not provide an indication of the type of jump that a dancer is performing.

In summary, the final system combined a total of 4 machine learning models that were applied to data collected using 6 wearable sensors. The first model was a human activity recognition model which was capable of detecting dance-specific jumps (bilateral, jumps, unilateral jumps and large jumps) and dance-specific leg lifting tasks (to the front, side and back), as well as transitions between these movements where a transition was anything that was not a jump or leg lift. The data generated from this machine learning model provided an indication of dancers' specific movement quantity. The remaining models provided an indication of dancers' movement quality during these movements of interest. Two models (1 for unilateral and 1 for bilateral jumps) were used to estimate the GRF during dancers' jumps. The final model was used to estimate the thigh elevation and lumbar spine sagittal angles when the dancers lifted their leg. The development of this wearable sensor system allowed for the measurement of dancers' movement quantity and quality within a field-based study, allowing for the exploration of the relationship between both movement quantity and quality with pain and pain related disability.

7.2.4 Applying this system to a field-based study: Challenges and limitations of the system

Interestingly, while we identified several studies that have applied human activity recognition to sporting tasks prior to the development of our models, there were no subsequent field-based studies identified that utilised the developed models to explore athletes' movement quantity in real-world settings. As a result, prior to the commencement of this research there was little published on the challenges that are faced with applying a wearable sensor / human activity recognition system within a field-based study.

Utilising data from 6 wearable sensors for a full day's training resulted in substantial computational times for data outputting, of approximately 10 hours, per dancer, per time point. Specifically, as the PhD scholar, I ran each set of data through the 4 individual models. Had a full day's training been utilised this would have resulted in a total of approximately 2080 hours of processing. Potentially, the use of a super-computer may have assisted in overcoming this limitation of the system, however this was not an option within this body of work. Future developments require software optimisation to allow more efficient processing of data, with a single step process and on readily available platforms, such as personal computers and smart devices.

Further, to improve the accuracy of our system within the field-based setting substantial data cleaning was applied, as described in Figure 6.2. The data cleaning process was performed manually, however was augmented by the movement quality machine learning outputs. Specifically, the outputs of the human activity recognition model were utilised to capture the data within the string of the wearable sensor data, which was then used within the machine learning models for the estimation of movement quality variables. For each jump that was identified, the machine learning model estimated the peak GRF, and the processing software also output a visual representation of the data. Similarly, for each leg lifting task, the machine learning model estimated the peak thigh elevation angle and lumbar spine sagittal angle, and the processing software also output a visual representation of the data. These data were all visually inspected. For the identified jumps, if the peak GRF was not identified or appeared small (<1.4BW) or large (>8BW) the visual representation of the jump was excluded from the analysis. For the identified leg lifts, if the peak thigh elevation angle was not identified or was greater than 160° the leg lift was excluded. Additionally, if the duration of a single leg lift was greater than 15000 frames (15 seconds) it was excluded from the analysis. The visual representation of all remaining trials of jumps and leg lifts were manually inspected by a single reviewer, and if the waveform was not consistent with standard jump GRF and leg lift kinematic profiles it was excluded from the analysis. This cleaning process resulted in the removal of all false positives. Therefore, while the accuracy of the model utilised was 77.1%, the final accuracy would have been substantially greater due to the described cleaning process.

Due to the substantial time demands of processing and cleaning the data in this thesis, it was determined that rather than utilising a full day's data, data from a single ballet class at each of the 4 time points would be included in the final study. We determined that this was appropriate as a proof-of-concept for monitoring of dancers' training loads as it provided capture of a class that the dancers consistently participated in. Given these resource limitations, the wearable sensor system developed and used within this thesis has demonstrated the potential for use within larger field-based studies, incorporating individual serial monitoring over time, allowing for the collection of large amounts of data to facilitate sophisticated temporal analytics such as complex systems approaches to further explore the complexities of individual dancer's pain and pain related disability (Bittencourt et al., 2016).

7.2.5 The future: Advancing the field

For larger studies to occur optimisation of the wearable sensor system is required to improve accuracy and usability. Given the substantial quantity of data processing and manual data cleaning required within the field-based study, a fully automated system with a greater degree of accuracy when utilised within the field is desirable. Suggestions of how this may be approached are described below, and can be broadly categorised into software and hardware considerations, and are described below.

7.2.5.1 Software considerations

Based on learnings from the current study, considerations surrounding the software utilised are: improving the accuracy of the machine learning models, considering both types of movement and optimising generalisability or individuality of the model, and optimising model integration with user-friendly devices.

7.2.5.2 Improving accuracy of machine learning models: types of movements

For the development of the human activity recogntion model, 23 dancers attended a data collection session in a ballet studio, where they performed a series of discrete movement tasks. These movements were then repeated within choreographed sequences.

Each dancer performed the same movements and the same choreographed sequences.Thus, while the diversity and range of jumps and leg lifts were common to what the dancers perform in their normal training, it is unlikely that every type of jump and leg lift movement was included. To allow for greater variability in movements, in future developments of machine learning models applied to wearable sensor data, researchers should consider fitting dancers with wearable sensors in their normal ballet classes to acquire the data for model development and validation. This would allow for a broader selection of jumps to be captured, as well as a broader capture of the movements of interest (i.e., a broad range of jumping movements) and other dance and non-dance movements (for example other movements such as pirouettes (when the dancer "spins" around on 1 leg), movements where the dancer is travelling across the studio or non-dance movements (such as walking or sitting). By capturing different dancers in different ballet classes, greater variation in the choreographed routines may improve the performance of the models when used in field-based settings. Additionally, the inclusion of data captured within contemporary dance classes, pointe work and rehearsals with varying repertoire would further promote generalisability of the model, allowing for use outside of a typical ballet class. This approach may further improve ecological validity of the field-based system, allowing for capture of a greater number of movements, thus improving both accuracy and practicality.

7.2.5.3 Improving accuracy of machine learning models: generalisability or individuality

Within the development of the current system, it was evident there was a range of accuracy across the sample of dancers, whereby the models performed extremely well for some dancers however not for others. It is therefore likely, but unclear, if this was also the case in the field-based study. Future model developments could aim to improve generalisability of the model or account for dancers' individual movement patterns. Specifically, model generalisability could be potentially improved by training models on a larger sample of dancers. This would increase the between dancer movement variability, thus developing models that are generalisable to a greater number of dancers. An alternative to developing machine learning models that are generalisable across a broad population of dancers, is to develop or refine models on individual dancers. Specifically for each dancer involved in the research, there is potential that machine learning models can be retrained and refined for each individual dancer within the research (Amrani, Micucci, & Napoletano, 2021). Such an approach would likely have the benefit of resulting in a more accurate system, when used for monitoring of this individual dancer (enabling the dancer to be their own baseline). This approach would allow individual differences of dancers to be accounted for, as the machine learning model would essentially be customised to the dancer that it was being used on. While this may increase accuracy, in order to be implemented training and testing data sets would need to be acquired for both movement quantity and quality models for every participant, as the model would only be able to used on the dancer it was developed on, and would not be easily generalisable to all dancers. Currently computational time likely would not allow for this and supercomputer systems, which may be difficult to access, would be required. There is however precedence for this approach through other applications of machine learning such as how social media retrains algorithms based on individual data. Therefore, while this approach may not be feasible currently, in the future there may be larger scope for it.

7.2.5.4 Improved integration with user friendly devices

The substantial data processing times could be improved by designing and optimising the machine learning models allowing for compatibility with personal computers and smart devices. Such developments would reduce the significant time burdens for researchers. Clinically, this would allow dancers, dance teachers and clinicians working in the field with the potential for real-time feedback on a dancers' movement quantity and quality to assist with the prevention of pain and pain related disability in dancers.

7.2.6 Hardware considerations

The wearable sensor system could be further optimised through the parameters that the sensors were set at and by looking at reducing the number of sensors. Importantly, with rapid advances in wearable sensor technology, some of the limitations and challenges presented in the field-based application of the wearable sensors may be overcome by advancing technology.

7.2.6.1 Sensor parameters

Within the current study, data was collected using Actigraph Link wearable sensors (Higgins, Higgins, & Vallabhajosula, 2021). The sensors were operating at 100Hz with the accelerometer, gyroscope and magnetometer all switched on. This was the highest collection frequency the wearable sensor enabled. However, collecting at this frequency and with these settings limits the battery life of the wearable sensors used to 8 hours, which is approximately the time of a single training day. Additionally, collecting at this frequency results in very large data sets, which increase processing times. At lower collection rates and with only the accelerometer switched on, the battery life of the sensor increases dramatically, and up to two weeks of data can be collected prior to the unit requiring charging. Therefore, a lower collection rate may be more appropriate for ongoing / serial monitoring of dancers' movement quantity and quality, unless hardware developments can improve battery life. Regardless, if lower frequencies were utilised for model development, machine learning models would need to be developed reflecting these parameters and this may influence accuracy. Specifically, given that the gold standard laboratory-based set ups collect at frequencies of 1000Hz for force platforms and 250Hz for optical motion capture systems, it could be hypothesised that the accuracy of the movement quality estimation would have reduced with a lower collection frequency. For example, a lower sample rate may result in loss of peak accelerations of high-speed movements and in turn the loss of peak GRFs, which have the potential for informing risk of pain development in future larger studies. However, these parameters and limitations are specific to this wearable sensor device, and the market for devices is constantly growing, with technology developing rapidly. Therefore, the identified challenges may soon become overcome or obsolete with continued advances in wearable sensor technology.

7.2.6.2 Number of sensors

As discussed in Section 7.2.2.5, future developments of machine learning models applied to wearable sensor data should consider using fewer sensors. Dance is highly aesthetic, and the attachment of multiple sensors has the potential to impede both the aesthetic qualities of dance and dancers' movement. This would both reduce the likelihood of dancers wearing such a system for the prolonged period that is required for serial monitoring. Further the use of multiple sensors would limit the utility of the system in a performance context. However, with improvements in wearable technology, smaller and smaller sensors are becoming available. In the future, if a sensor of similar size and form as a Band-Aid was developed there would be greater scope for the use of multiple sensors. However, from a practicality perspective for researchers, the use of multiple sensors still requires greater set up, processing and computational demands. Further, more sensors provide greater scope for more technology malfunctions, and missing data potential. Currently, a greater number of sensors is also more costly to purchase and maintain, however again, with growth in the wearable sensor market the purchase and running costs of wearable sensors is reducing.

Within the context of dance, the ideal system would likely use only a single sensor. Based on the results of Study 1, the most accurate single sensor model used the data from the sacrum sensor. At the second level of classification, with the inclusion of transitions this performed with 70% accuracy. However, 70% accuracy is lower than that demonstrated for machine learning models in several other sports which have used only a single sensor, as shown in Table 2.3 and Table 2.4 (Cust et al., 2019). Regardless, these results should be considered in future developments as this sensor location may be ideal for dancers. A sacrum sensor is easily concealed, thus neither impedes dancers' movements nor the aesthetics of dance. As well as being the best single sensor for the human activity recognition model, the sacrum sensor was the most optimal model for estimation of GRF during jumping also performed with an acceptable degree of accuracy. Therefore, use of this single sensor would allow for quantification of dance-specific movements and estimation of the movement quality variable of GRF. However, a single sacrum sensor system would be insufficient to estimate joint angles during leg lifting tasks. Based on the results of Study 2B, the most accurate model for the estimation of thigh elevation and lumbar spine sagittal angles during leg lifting tasks required data from the bilateral thigh sensors. Indeed, all top 10 performing models utilised thigh sensor data. Therefore, based on the movements investigated, the results of this thesis suggests that the minimum number of sensors that would be required for a wearable sensor system to comprehensively measure dancers movement quantity and quality involving jumping and leg lifting would be 3 sensors, located at the sacrum and bilateral thighs. However such a system would not have acceptable accuracy at measuring movment quantity, as described in Section 7.2.2.5.

Within this body of work, dancers and dance teachers were not surveyed in relation to the acceptability of wearing the wearable sensors in dance class and performance. However, with continued advances in wearable sensor technology, where manufacturers are reducing the size of sensors and developing the ability to build sensors into clothing, a sacrum worn sensor has the potential to be built into a dancer's leotard, thus minimising any potential aesthetic and movement interference. Currently, this may be similar to a sports person wearing a wearable sensor in a built-in pocket in their shirt. However, advances in technology may allow for the potential of improved accessibility and wearability of the sensors for a dancer, similar to the small, Band-Aid style sensors described above. Not only would they promote easier field-based serial monitoring of dancers for research purposes, they would provide opportunity for real-world use by clinicians and dance teachers to monitor dancers in their normal training.

7.3 The relationship of dancers' movement quantity and quality with pain and pain related disability: Where the field currently sits.

Recent publications exploring the relationship of dancers' pain with movement quantity has analysed the relationship looking at pain under the construct of "injury" and considered the number of "injuries" present. Generally there is a lack of consensus surrounding the relationship between dancers' movement quantity and "injury", as described in Chapter 2. While some studies have identified injury rates mirroring fluctuations in movement quantity, either by total number of hours or total number of sessions per week, others have shown no relationship disability (Boeding et al., 2019; Cahalan et al., 2019; Cahalan, Kearney, et al., 2018; Jeffries et al., 2020; L. Lee et al., 2017; Shaw et al., 2021; Volkova & Kenny, 2020). The variable relationships demonstrated may, in part, reflect the limitations of the current body of literature in this field. Specifically, dependent on how it is defined, the construct of "injury" may not truly capture the burden of the problem of musculoskeletal pain amongst dancers, both at a population level and at an individual level (Kenny et al., 2018). Further, while the number of injuries experienced at a time point provides an indication at a group level of how movement quantity may relate with the incidence of injury within dance, it does not provide any indication of a dancer's individual experience of pain. Thus, the current body of literature is limited to group-level analysis, without consideration of the individual, when pain is a highly individual experience (Caneiro et al., 2021).

7.3.1 Understanding of pain via an "injury" model

The majority of the dance literature exploring pain in dancers view pain using an "injury" model. Within previous work exploring the relationship between dancers' movement quantity and "injury", injury definitions have also been variable. Research exploring the relationship of professional dancers' movement quantity and "injury" utilised medical attention and time loss definitions, and "injury" recorded by in house medical staff. Professional dance companies frequently have medical teams onsite, which allows easy access to these resources, but this is less common in pre-professional settings (Kenny et al., 2018). Additionally, pre-professional dancers do not consistently access services from health care providers when experiencing pain (Wang & Russell, 2018). Therefore, the use of a "medical attention" definition may not be appropriate for use in pre-professional dancers, as it would likely not capture the full burden of the problem of musculoskeletal pain in this cohort. This may be why researchers exploring the relationship of movement quantity with "injury" in pre-professional dancers have utilised dancers' self-reported "injury". Some of these studies have included a time loss definition, whereby within their self-report dancers include the number of days they cease training due to their injury. However, it is widely cited that dancers frequently continue to dance while experiencing pain or injury, thus time-loss definitions may not truly capture a dancer's pain experience (Anderson & Hanrahan, 2008; Encarnacion et al., 2000; Kenny et al., 2018; Mainwaring & Finney, 2017).

Importantly, as detailed in Chapter 2, there is a need to understand musculoskeletal pain outside of the "injury" model, as this term implies the presence of anatomical level tissue damage, which frequently does not correlate well with a person's pain experience (Caneiro et al., 2021; Hainline et al., 2017). Tissue damage tends to occur when the load applied to tissue exceeds the tissue's capacity to tolerate that load, and can be associated with pain (Caneiro et al., 2021). For example in an acute ligament tear, where tissue is exposed to a sudden traumatic event and cannot withstand this load a person can experience substantial pain (Caneiro et al., 2021). Similarly, pain associated with a change in loading or repetitive loading over time may be related to a stress fracture (Caneiro et al., 2021). However, it is broadly recognised that pain can exist in the absence of tissue damage, and conversely, changes to anatomical structure can exist in the absence of pain (Hainline et al., 2017). Indeed, previous research in dancers, has demonstrated that radiological evidence of hip morphological and pathological changes and lower limb tendinopathic changes do not correlate with pain, and instead are considered to be adaptive changes to the tissue based on the physical occupational related exposures of dance (Comin et al., 2013; Mayes et al., 2016a, 2016b, 2016c, 2016d; Mayes, Smith, & Cook, 2018). Thus pain that presents without clear evidence of a pathoanatomical basis should not be labelled as injury. Similarly, anatomical changes that may be adaptive in nature should not be labelled as injury. As a result there is a need to move away from the "injury" model and look towards a model of pain (Caneiro et al., 2021).

Additionally, in determining the relationship of movement quantity with pain related disability, the majority of the current body of literature utilises the number of "injuries" present in a sample of dancers at a time point within their analysis. In essence, this method of capturing the presence of pain, looks at pain or injury as a dichotomous variable, where either the dancer is, or is not, experiencing pain. While this provides capture of the problem at a group level, it does not provide insight to the individual experience of a dancer's pain and pain related disability.

7.3.2 The dancers' experience of pain

To overcome the limitations of the "injury" model, within this research we adopted more comprehensive measures of pain and related disability. Three separate classifications for musculoskeletal pain were utilised: 1) Acute traumatic event referred to dancer reported incidents such as ankle sprains, muscle tears and fractures, 2) Pain was considered via subjective reporting of any musculoskeletal pain (location and intensity) in the event where there was no acute inciting incident, and the dancer was able to continue to dance and participate in normal activities of daily living, and 3) Pain related disability was considered when a dancer subjectively reported pain that either required a time period of modified participation or complete cessation of dance training and performance and that impacted the dancer's normal activities of daily living outside of dance. Both pain and pain related disability could include "overuse" related presentations.

The presence of pain and pain related disability was only dichotomised to describe the sample. Almost all the dancers in the study experienced pain at some point during the 12-week period and half of these dancers' pain was considered disabling (PSFS < 7). Interestingly, only 2 of the dancers reported pain as a result of an acute traumatic event, one of these was due to a patella dislocation and the other a shoulder dislocation. Both of these dancers required a period of complete rest from dance due to these events. However, they were the only dancers within this study who required complete cessation of dance activity due to pain. These results were consistent with those in other samples of pre-professional dancers. In a sample of Australian university level, pre-professional ballet and contemporary dance students (n=17), of the 119 "injuries" experienced over the duration of their 3-year dance course, only 7 injuries were considered traumatic and only 3 injuries required time loss. It was unclear if those requiring time loss were classified as traumatic (Fuller et al., 2020). However, 56% of the injuries were disabling, requiring modification to dancers training (Fuller et al., 2020). Thus the results of this thesis and previous work on Australian pre-professional dancers suggest that while pain is experienced by all dancers, approximately half experience some degree of pain related disability. However, those who are disabled by their pain generally continued to engage in their training under modified conditions rather than completely ceasing dancing activity. This supports previous suggestions that a "time loss injury" definition does not truly capture the problem of musculoskeletal pain in pre-professional dancers (Kenny et al., 2018). Additionally, the low numbers of acute traumatic events, which would have resulted in definite tissue damage, supports the suggestion of a need to step away from an "injury" model (Caneiro et al., 2021; Hainline et al., 2017).

Within the analysis for Study 3 (Chapter 6), rather than utilising the total number of pain presentations at each time point, dancers' pain experience was considered. Specifically, the analyses considered dancers' pain severity and pain related disability measured at each time-point using the Numerical Rating Scale (NRS) and Patient Specific Functional Scale (PSFS).

Despite the high prevalence of pain, as a group the dancers in the current study reported relatively low levels of both pain severity and pain related disability. Average NRS scores ranged from 3.1-3.5/10 and average PSFS scores ranged from 7.8-8.1/10 across the 4 time points. The average pain severity scores demonstrated are consistent with those seen in professional and non-professional ballet, jazz and street dance dancers, where the majority of dancers rated their pain as mild (Diogo, Ribas, & Skare, 2016). However the average pain severity is low compared to other reports in professional ballet and contemporary dancers, where the majority of dancers experiencing pain reported moderate to severe levels of pain (Dore & Guerra, 2007; Jacobs et al., 2016). The reason for these low levels of pain severity and pain related disability in this sample of dancers is unclear, however previous work has suggested that, consistent with professional athletes, professional dancers demonstrate higher pain tolerance than controls (Tajet-Foxell & Rose, 1995). Two possible explanations were hypothesised for these findings (Tajet-Foxell & Rose, 1995). The first theory was biological in nature, where the greater pain thresholds demonstrated by dancers were potentially due to increased levels of endogenous opioids resulting from their physical training and increased fitness (Tajet-Foxell & Rose, 1995). Their second theory reflected dancers' cognitions developed within their training, suggesting dancers explore boundaries with extreme physical activity and pain in a way that non-dancers do not, providing them with a perception of control in relation to pain when they are dancing (Tajet-Foxell & Rose, 1995). The theme of a perception of control was reflected in the findings of the adjunct study presented in Appendix O, where dancers reported actions aligning with controlling and protecting the lower back during dance-specific low back movements.

An alternative theory is that the relatively low levels of pain severity and disability may reflect how dancers perceived their pain. Previous publications have described how dancers differentiate between "performance pain" and "injury pain" (Anderson & Hanrahan, 2008; Harrison & Ruddock-Hudson, 2017; Thomas & Tarr, 2009). It is possible that the majority of dancers perceived their pain as “performance pain” which is considered harmless, tolerable and short lived pain, of low intensity, as opposed to “injury pain”, which is considered threatening, dangerous and intolerable and is difficult to control, limiting dancing and is severe in intensity (Anderson & Hanrahan, 2008; Harrison & Ruddock-Hudson, 2017; Thomas & Tarr, 2009). However, this theory is speculative and requires further research. Regardless, the average pain and disability scores demonstrated in this thesis highlight the importance of consideration of a dancer’s individual experiences of pain as opposed to the number of pain presentations within a group. Further, the relatively low levels of pain severity and pain related disability may have influenced the associations identified in this thesis.

While no associations between pain severity and both movement quantity and quality were apparent, there was evidence of some modest, group level associations between pain related disability and movement quantity and quality. These results suggest that irrespective of pain intensity dancers continue to engage in their training normally. However, when their pain becomes disabling, they continue to dance, but with modifications. Specifically, greater levels of pain related disability were associated with more time spent in light intensity activity, and this time appeared to be taken from moderate intensity activity. Further, greater levels of pain related disability were associated with fewer leg lifts to the front and overall, and less time spent performing leg lifts to the front. These results potentially challenge the notion of a culture in dance where dancers ignore and “push through” pain in order to continue dancing (Encarnacion et al., 2000; Lampe, Borgetto, Groneberg, & Wanke, 2018; Tajet-Foxell & Rose, 1995). Rather than ignoring and “pushing through” pain, the dancers modified their training, making potentially adaptive changes. Specifically, even with relatively low levels of pain and disability, the dancers in our study demonstrated what appears to be an adaptive response to disabling pain whereby they reduced their movement quantity overall, and during leg lifts to allow themselves to continue to engage in their dancing. However, in relation to movement quality, greater pain related disability was associated with greater thigh elevation angles during side leg lifts. Within the review of literature, no other studies exploring changes in movement quality with changes in dancers’ pain related disability were identified. However it has been recognised that the large ranges of movement that dancers achieve during side leg lifts may be associated with the development of hip pain secondary to increases in joint loading (Han et al., 2019). Thus, it could be hypothesised that when experiencing higher levels of pain related disability, the dancers, at a group level, were modifying their training behaviours in ways which may reduce general load (movement quantity) while also increasing specific joint load (thigh elevation angle during leg lifts). These findings potentially reflect the continuous juggling act that dancers are faced with in the management of pain and disability, where they are persistently aiming to continue to engage in their valued activity, while either coping with, or compensating for, their pain. Further research, including a more diverse array of movements is needed to explore this hypothesis.

Interestingly, there was no association demonstrated between pain related disability and both the quantity and quality of dancers jumping activity. This came as a surprise as previous literature suggesting jumping, and the associated GRF, as one of the leading mechanisms of "injury" amongst dancers (Allen et al., 2012; Mattiussi et al., 2021; Mattiussi et al., 2021). Specifically, in a 5-year epidemiological study, published during the course of this doctoral thesis, 27% of "time-loss injuries" experienced by professional ballet dancers were linked to jumping (Mattiussi et al., 2021). "Time-loss injury" was defined as injury requiring modification or cessation of dance training and performance. Potentially, had the dancers in the current work been monitored daily and for a longer time period an association between movement quantity and quality of dancers jumping activity would have been established. Additionally, research has demonstrated that professional contemporary and ballet dancers perceive jumping as one of the most pain provocative activities within their training (Vassallo et al., 2017), thus it would be expected that when experiencing pain dancers may alter their jumping behaviour.

The lack of association of jumping movement quantity and quality with pain and pain related disability, challenge findings demonstrated in cross-sectional studies comparing dancers with and without anterior knee pain suggesting that those with pain demonstrated greater peak GRF during a ballet specific jumps (grand jeté mean difference=1.58BW, $P<0.001$, echappe saute mean difference 0.2BW, CI: 0.08, 0.32) (Fietzer et al., 2012; Peng et al., 2015). However, both of these studies only considered pain presence rather than pain severity, and were performed on a single day. Additionally, they were limited to laboratory-based settings, thus reducing the ecological validity. In contrast, the findings presented in this thesis considered changes in pain severity at 4 different time-points and data was collected within the dancers normal training environment, thus reflecting their normal training behaviours when experiencing pain. Notably however, the dancers in the above-mentioned studies were experiencing knee pain (Fietzer et al., 2012; Peng et al., 2015), whilst pain location was not accounted for in Study 3's analysis. It is possible that different movement quality factors are linked to specific pain areas, for example knee pain may be linked to changes in GRF and low back pain linked to lumbar spine kinematics during leg lifts to the back. Another explanation for the lack of association of jumping movement quantity and quality with pain and pain related disability, may relate to the aforementioned low levels of pain and disability observed in this thesis. Potentially, the threshold for marked changes in movement in response to pain was not met, in line with previous experimental research, where changes in movement were only demonstrated at higher pain intensities (Henriksen et al., 2011).

7.3.3 Advancing the field: Considerations for continuing to improve our understanding of the complexities of dancers' pain and pain related disability

While this thesis employed the use of more comprehensive measures of pain compared to previous work, and considered both changes in pain severity and pain related disability, there are a number of considerations for future work to assist in understanding the complex nature of a dancer's pain and disability. Specifically, individualised analysis incorporating serial monitoring of both movement quantity and quality, as well as other salient risk factors would be useful. Additionally, accounting for variation in pain location and the task that dancers selected in the PSFS, both within and between dancers should be considered. Consideration of these factors may assist in understanding dancers' pain at an individual level.

7.3.4 Understanding pain at an individual level

While some associations demonstrated in Study 3 were considered statistically significant, they should be regarded with caution, as they reflect group level associations as opposed to that of the individual. Essentially, it cannot be assumed that all dancers were employing the strategies in response to pain, as pain is a highly individual experience. However, the results of the within person analysis demonstrated no evidence of within person relationships of movement quantity and quality with either pain severity or pain related disability. The lack of within person associations may be due to the study design. Having only 4 time-points of data collection over a 12-week period and capturing only a single ballet class likely reduced the available amount of information to demonstrate associations at the level of the individual dancer. Future work should consider daily monitoring of dancers' over a prolonged time period. However, this study provides a proof-of-concept that the field-based system developed and used could allow for future research incorporating continuous, serial monitoring of dancers' movement quantity and quality.

7.3.4.1 Variation in pain location

Consistent with previous literature, the foot/ankle was the most common location for dancers' pain, followed by the lower back. However, in Study 3 (Chapter 6) pain severity and pain related disability was considered irrespective of pain location. At each time point, dancers were able to report different pain locations. Allowing for this variation in reporting was considered important, as dancers commonly experience pain in different locations at different times. Fuller et al., 2020 revealed that 75% of subsequent "injuries" in pre-professional dancers are at a different site. Therefore, accounting for pain location within the analysis may influence results and provide a more comprehensive understanding of the relationship of dancers' movement quantity and quality with pain and pain related disability, both between and within dancers. Potentially, both movement quantity and quality could be linked with the anatomical location of pain. For example, it could be hypothesised that dancers experiencing foot and ankle pain may modify their jumping movement quantity and quality, potentially reducing the number of jumps or landing their jumps differently to dancers with lower back pain. Similarly, an individual dancer may land a jump differently when she is experiencing foot and ankle pain at 1 time point, compared to if she is experiencing lower back pain at a different time point. Therefore, future research might better elucidate understanding the relationship between movement and pain if it addresses specific pain locations.

7.3.4.2 Variation in task selection in the Patient Specific Functional Scale

While dancers selected specific tasks that they were finding difficult to perform due to their pain to provide ratings on in Study 3, these were not considered in the analysis. Rather the score that the dancer applied to the task was utilised as a measure of disability. As for pain location, dancers were able to select different tasks at each time point. However, accounting for the specific tasks that dancers select may influence results. For example, it could be hypothesised that a dancer with lower back pain may select back leg lifts as a movement they are having difficulty with in the PSFS. As a result, they may reduce the number of leg lifts to the back, or modify their movement quality during leg lifts to the back, utilising lower thigh elevation and lumbar spine sagittal angles, compared with a dancer who is experiencing foot and ankle pain who has identified jumping as difficult on the PSFS due to their pain. Similarly, an individual dancer may demonstrate different movement quantity and quality at a time period when she identifies leg lifts as difficult on the PSFS compared to when she identifies jumping as difficult on the PSFS. Future mixed methods studies exploring if modifications in movement behaviour are conscious or subconscious would also allow further exploration of this concept. Additionally, qualitatively exploring dancers' perceptions of their pain, disability and dance performance in conjunction with the quantitative measurement that the system developed in this thesis provides allows the potential of seeing if dancers' perceptions of pain match their movement behaviours.

7.3.4.3 The inclusion of other domains

Given the physical nature of a dancer's training and the long-held belief that this is related to the often high rates of pain and disability, this thesis explored the domains of dancers' movement quantity and quality relative to pain and disability. However, pain development, and the trajectory that a person's pain takes is influenced by more than movement parameters (Caneiro et al., 2021; O'Sullivan et al., 2018). Therefore, to advance our understanding of the complexities of pain in dancers, future longitudinal studies should also include serial monitoring of other domains that may influence pain and disability. Specifically concurrent serial monitoring of dancers psychological and lifestyle factors, such as mood, cognitions, coping responses, fatigue and sleep would be useful. It is plausible that these factors, and the potential multidirectional relationships that they may have with both movement quantity and quality, may influence dancers' pain development, their behaviours and coping responses when they experience pain and the trajectory their pain takes. Additionally, the incorporation of serial monitoring of "session RPE" integrating wearable sensor measures of specific training loads, such as the number of jumps or leg lifts, with dancers' perception of effort during training would continue to strengthen this research (Jeffries et al., 2016). This would allow for further analysis of the complex interactions between different domains to provide a comprehensive understanding of the risks for the development of an individual dancer's pain and the responses that a dancer has when experiencing pain and disability.

7.4 Strengths and limitations of thesis

This thesis includes work of notable strength. The wearable sensor system developed across Studies 1 and 2, presented in Chapters 3 to 5, employed innovative techniques to objectively quantifying movement quantity and quality in dancers. The final developed system was capable of detecting dance-specific movement tasks and their associated movement quality that have been considered relevant in the development of pain and disability by researchers, dancers and clinicians alike. While the degree of accuracy was considered acceptable, it was also enhanced via significant data cleaning efforts when applied to the field-based study in Study 3 (Chapter 6). In applying this system to a field-based study the thesis reports on the first longitudinal research project within the field that had considered both dancers movement quantity and quality relative to pain and disability.

Several limitations of the thesis have been identified and highlighted throughout this chapter. In relation to the wearable sensor system developed in Study 1 and 2 and described in Section 7.2.4 of this chapter, the limitations described surrounding accuracy and usability of the system likely reflect the unique nature of this work, where the field of machine learning is rapidly growing, and methodological advances are continuously being explored to facilitate improvements in model developments. As described in Section 7.3.3 of this chapter, there were challenges when applying the wearable sensor system to a longitudinal, field-based study resulted in collecting data from just 4 single dance classes as opposed to a full day's training at each time point of data collection. Repeated measures at only 4 time points over the 12-week period, reduced the available information to elucidate associations within individual dancers.

All 3 studies were also limited to the inclusion of only female pre-professional ballet and contemporary dancers. The inclusion of only female dancers for the machine learning model development, limits the application of the wearable sensor system to female pre-professional dancers. Future developments should consider the inclusion of data from a more diverse selection of dancers including male dancers, recreational dancers, and professional dancers. The inclusion of only female dancers for the field-based study in Study 3 reflected the differences in participation rates of male and female dancers at a pre-professional level, however may have influenced results. Typically, in Australian university dance settings there are fewer males than females enrolled in dance programs (Fuller et al., 2020). Indeed, less than 10% of dancers in the dance program where dancers for this thesis were recruited from were male. However, as other training facilities and professional dance companies may have similar numbers of male and female dancers, future research should include male dancers. Further, limiting the sample for Study 3 to a single dance institution reduces generalisability of the results, as training regimens across facilities may influence movement demands and thus associations with pain and related disability. Future work could usefully engage multicentre collaborations to capture recreational through to professional dancers at multiple institutions internationally.

7.5 Beyond research: Real-world, clinical application of a wearable sensor system

Looking beyond the scope of research, the ultimate goal of a system such as the one developed in this thesis is a fully automated system which can be used by dancers within their normal training, allowing for real-time monitoring of movement quantity and quality. By integrating a single wearable sensor with user friendly software on a dancer's smart device, this technology could be used in the prevention of musculoskeletal pain and disability. However, to allow for such application, further work in this space is required. As well as optimising wearable sensor systems to promote consumer usability, further research utilising the system to continue exploring the complex interactions between movement quantity and quality and pain related disability is needed.

7.6 Conclusions of thesis

The novel field-based sensor system developed and validated in this thesis demonstrated it could provide quantitative information on both movement quantity and quality in a real-world environment. While further optimisation of the technology used is required to enhance both accuracy and practicality, this thesis demonstrates a proof-of-concept for larger, longitudinal field-based research to occur. By applying the wearable sensor system to a field-based study, insight was sought into how dancers with disabling pain may adapt the way they move to reduce load, allowing them to continue to engage in their dance training. However, it is unlikely that these same responses are utilised by all dancers when faced with pain and pain related disability. Rather, it is likely that complex interactions between movement quantity and quality, as well as other biopsychosocial factors, that are unique to each individual, influence a person's pain development and coping responses to pain. Future application of wearable sensor technology provides the opportunity for clinicians to gain a deeper insight into these complex interrelationships, to better inform person centred care.

The outcomes of this thesis provide scope for frequent, field-based, serial measures of movement quantity and quality in a dancer's everyday training. Access to such measurement tools would provide an opportunity for collection of the substantial data requirements needed for modelling the complexity of interrelationships between movement, pain, disability and other factors such as psychological and lifestyle factors, using sophisticated analytics such as complex systems approaches (Bittencourt et al., 2016). This would also create opportunities within clinical research and practice for assessment and monitoring of individual dancers, and detecting shifts in individual dancer movement behaviours in response to treatment or advice.

References

Abbott, J. H., & Schmitt, J. (2014). Minimum important differences for the patient-specific functional scale, 4 region-specific outcome measures, and the numeric pain rating scale. *J Orthop Sports Phys Ther, 44*(8), 560-564. doi:10.2519/jospt.2014.5248

Adelsberger, R., & Troster, G. (2013, 6-9 May 2013). *Experts lift differently: Classification of weight-lifting athletes.* Paper presented at the 2013 IEEE International Conference on Body Sensor Networks, Cambridge, MA, USA.

Air, M. E. (2013). Psychological distress among dancers seeking outpatient treatment for musculoskeletal injury. *J Dance Med Sci, 17*(3), 115-125. doi:10.12678/1089-313x.17.3.115

Alcantara, R. S., Day, E. M., Hahn, M. E., & Grabowski, A. M. (2021). Sacral acceleration can predict whole-body kinetics and stride kinematics across running speeds. *PeerJ, 9*, e11199. doi:10.7717/peerj.11199

Allen, N., Nevill, A., Brooks, J., Koutedakis, Y., & Wyon, M. (2012). Ballet injuries: Injury incidence and severity over 1 year. *J Orthop Sports Phys Ther, 42*(9), 781-790. doi:10.2519/jospt.2012.3893

Amrani, H., Micucci, D., & Napoletano, P. (2021, 10-15 Jan. 2021). *Personalized models in human activity recognition using deep learning.* Paper presented at the 2020 25th International Conference on Pattern Recognition (ICPR).

Anand, A., Sharma, M., Srivastava, R., Kaligounder, L., & Prakash, D. (2017). *Wearable motion sensor based analysis of swing sports.* Paper presented at the 16th IEEE International Conference on Machine Learning and Applications (ICMLA).

Ancillao, A., Tedesco, S., Barton, J., & O'Flynn, B. (2018). Indirect measurement of ground reaction forces and moments by means of wearable inertial sensors: A systematic review. *Sensors (Basel), 18*(8). doi:10.3390/s18082564

Anderson, R., & Hanrahan, S. J. (2008). Dancing in pain: Pain appraisal and coping in dancers. *J Dance Med Sci, 12*(1), 9-16.

Argent, R., Drummond, S., Remus, A., O'Reilly, M., & Caulfield, B. (2019). Evaluating the use of machine learning in the assessment of joint angle using a single inertial sensor. *J Rehabil Assist Technol Eng, 6*, 2055668319868544. doi:10.1177/2055668319868544

Attal, F., Mohammed, S., Dedabrishvili, M., Chamroukhi, F., Oukhellou, L., & Amirat, Y. (2015). Physical human activity recognition using wearable sensors. *Sensors (Basel), 15*(12), 31314-31338. doi:10.3390/s151229858

Australian Sports Commission (2021). Ausplay results. Retrieved from https://www.clearinghouseforsport.gov.au/research/ausplay/results

Baida, S. R., Gore, S. J., Franklyn-Miller, A. D., & Moran, K. A. (2018). Does the amount of lower extremity movement variability differ between injured and uninjured populations? A systematic review. *Scand J Med Sci Sports, 28*(4), 1320-1338. doi:10.1111/sms.13036

Bauer, C. M., Rast, F. M., Ernst, M. J., Meichtry, A., Kool, J., Rissanen, S. M., . . . Kankaanpää, M. (2017). The effect of muscle fatigue and low back pain on lumbar movement variability and complexity. *J Electromyogr Kinesiol, 33*, 94-102. doi:https://doi.org/10.1016/j.jelekin.2017.02.003

Benson, L. C., Clermont, C. A., Bosnjak, E., & Ferber, R. (2018). The use of wearable devices for walking and running gait analysis outside of the lab: A systematic review. *Gait Posture, 63*, 124-138. doi:10.1016/j.gaitpost.2018.04.047

Benson, L. C., Tait, T. J., Befus, K., Choi, J., Hillson, C., Stilling, C., . . . Emery, C. A. (2020). Validation of a commercially available inertial measurement unit for recording jump load in youth basketball players. *J Sports Sci, 38*(8), 928-936. doi:10.1080/02640414.2020.1737360

Bessone, V., Petrat, J., & Schwirtz, A. (2019). Ground reaction forces and kinematics of ski jump landing using wearable sensors. *Sensors (Basel), 19*(9). doi:10.3390/s19092011

Biernacki, J. L., d'Hemecourt, P. A., Stracciolini, A., Owen, M., & Sugimoto, D. (2020). Ultrasound alpha angles and hip pain and function in female elite adolescent ballet dancers. *J Dance Med Sci, 24*(3), 99-104. doi:10.12678/1089-313x.24.3.99

Biernacki, J. L., Stracciolini, A., Griffith, K. L., D'Hemecourt, P. A., Owen, M., & Sugimoto, D. (2018). Association between coping skills, past injury and hip pain and function in adolescent elite female ballet dancers. *Phys Sportsmed*, 1-8. doi:10.1080/00913847.2018.1423853

Bittencourt, N. F. N., Meeuwisse, W. H., Mendonça, L. D., Nettel-Aguirre, A., Ocarino, J. M., & Fonseca, S. T. (2016). Complex systems approach for sports injuries: Moving from risk factor identification to injury pattern recognition—narrative review and new concept. *Br J Sports Med, 50*(21), 1309-1314. doi:10.1136/bjsports-2015-095850

Boeding, J. R. E., Visser, E., Meuffels, D. E., & de Vos, R. J. (2019). Is training load associated with symptoms of overuse injury in dancers? A prospective observational study. *J Dance Med Sci, 23*(1), 11-16. doi:10.12678/1089-313x.23.1.11

Bowerman, E., Whatman, C., Harris, N., & Bradshaw, E. (2015). A review of the risk factors for lower extremity overuse injuries in young elite female ballet dancers. *J Dance Med Sci, 19*(2), 51-56. doi:10.12678/1089-313X.19.2.51

Bowerman, E., Whatman, C., Harris, N., Bradshaw, E., & Karin, J. (2014). Are maturation, growth and lower extremity alignment associated with overuse injury in elite adolescent ballet dancers? *Phys Ther Sport, 15*(4), 234-241. doi:10.1016/j.ptsp.2013.12.014

Brock, H., & Ohgi, Y. (2017). Assessing motion style errors in ski jumping using inertial sensor devices. *IEEE Sensors Journal, 17*(12), 3794-3804. doi:10.1109/JSEN.2017.2699162

Brock, H., Ohgi, Y., & Lee, J. (2017). *Learning to judge like a human: Convolutional networks for classification of ski jumping errors.* Paper presented at the 2017 ACM International Symposium on Wearable Computers- ISWC '17.

Bronner, S. (2012). Differences in segmental coordination and postural control in a multi-joint dance movement: Developpe arabesque. *J Dance Med Sci, 16*(1), 26-35.

Bronner, S., & Ojofeitimi, S. (2011). Pelvis and hip three-dimensional kinematics in grand battement movements. *J Dance Med Sci, 15*(1), 23-30.

Bronner, S., & Shippen, J. (2015). Biomechanical metrics of aesthetic perception in dance. *Exp Brain Res, 233*(12), 3565-3581. doi:10.1007/s00221-015-4424-4

Buckley, C., O'Reilly, M. A., Whelan, D., Farrell, A. V., Clark, L., Longo, V., . . . Caulfield, B. (2017). *Binary classification of running fatigue using a single inertial measurement unit.* Paper presented at the IEEE 14th International Conference on Wearable and Implantable Body Sensor Networks (BSN), Eindhoven, Netherlands.

Bulling, A., Blanke, U., & Schiele, B. (2014). A tutorial on human activity recognition using body-worn inertial sensors. *ACM Computing Surveys, 46*(3), 1-33. doi:10.1145/2499621

Büthe, L., Blanke, U., Capkevics, H., & Tröster, G. (2016, 14-17 June 2016). *A wearable sensing system for timing analysis in tennis.* Paper presented at the 2016 IEEE 13th International Conference on Wearable and Implantable Body Sensor Networks (BSN).

Byhring, S., & Bo, K. (2002). Musculoskeletal injuries in the norwegian national ballet: A prospective cohort study. *Scand J Med Sci Sports, 12*(6), 365-370.

Cahalan, R., Bargary, N., & O'Sullivan, K. (2018). Pain and injury in elite adolescent irish dancers: A cross-sectional study. *J Dance Med Sci, 22*(2), 91-99. doi:10.12678/1089-313x.22.2.91

Cahalan, R., Bargary, N., & O'Sullivan, K. (2019). Dance exposure, general health, sleep and injury in elite adolescent irish dancers: A prospective study. *Phys Ther Sport, 40,* 153-159. doi:10.1016/j.ptsp.2019.09.008

Cahalan, R., Kearney, P., Ni Bhriain, O., Redding, E., Quin, E., McLaughlin, L. C., & K, O. S. (2018). Dance exposure, wellbeing and injury in collegiate irish and contemporary dancers: A prospective study. *Phys Ther Sport, 34*, 77-83. doi:10.1016/j.ptsp.2018.09.006

Cahalan, R., & O'Sullivan, K. (2013). Injury in professional irish dancers. *J Dance Med Sci, 17*(4), 150-158. doi:10.12678/1089-313x.17.4.150

Cahalan, R., O'Sullivan, P., Purtill, H., Bargary, N., Ni Bhriain, O., & O'Sullivan, K. (2016). Inability to perform because of pain/injury in elite adult irish dance: A prospective investigation of contributing factors. *Scand J Med Sci Sports, 26*(6), 694-702. doi:10.1111/sms.12492

Caine, D., Bergeron, G., Goodwin, B. J., Thomas, J., Caine, C. G., Steinfeld, S., . . . Andre, S. (2016). A survey of injuries affecting pre-professional ballet dancers. *J Dance Med Sci, 20*(3), 115-126. doi:10.12678/1089-313X.20.3.115

Camomilla, V., Bergamini, E., Fantozzi, S., & Vannozzi, G. (2018). Trends supporting the in-field use of wearable inertial sensors for sport performance evaluation: A systematic review. *Sensors (Basel), 18*(3). doi:10.3390/s18030873

Campoy, F. A., Coelho, L. R., Bastos, F. N., Netto Junior, J., Vanderlei, L. C., Monteiro, H. L., . . . Pastre, C. M. (2011). Investigation of risk factors and characteristics of dance injuries. *Clin J Sport Med, 21*(6), 493-498.

Caneiro, J. P., Alaiti, R. K., Fukusawa, L., Hespanhol, L., Brukner, P., & Sullivan, P. P. B. (2021). There is more to pain than tissue damage: Eight principles to guide care of acute non-traumatic pain in sport. *British Journal of Sports Medicine, 55*(2), 75. doi:10.1136/bjsports-2019-101705

Chai, T., & Draxler, R. R. (2014). Root mean square error (rmse) or mean absolute error (mae)? – arguments against avoiding rmse in the literature. *Geosci Model Dev, 7*(3), 1247-1250. doi:10.5194/gmd-7-1247-2014

Chambers, R., Gabbett, T. J., Cole, M. H., & Beard, A. (2015). The use of wearable microsensors to quantify sport-specific movements. *Sports Med, 45*(7), 1065-1081. doi:10.1007/s40279-015-0332-9

Chambers, R. M., Gabbett, T. J., & Cole, M. H. (2019). Validity of a microsensor-based algorithm for detecting scrum events in rugby union. *Int J Sports Physiol Perform, 14*(2), 176-182. doi:10.1123/ijspp.2018-0222

Chambers, R. M., Gabbett, T. J., Gupta, R., Josman, C., Bown, R., Stridgeon, P., & Cole, M. H. (2019). Automatic detection of one-on-one tackles and ruck events using microtechnology in rugby union. *J Sci Med Sport, 22*(7), 827-832. doi:10.1016/j.jsams.2019.01.001

Chang, M., Halaki, M., Adams, R., Cobley, S., Lee, K. Y., & O'Dwyer, N. (2016). An exploration of the perception of dance and its relation to biomechanical motion: A systematic review and narrative synthesis. *J Dance Med Sci, 20*(3), 127-136. doi:10.12678/1089-313x.20.3.127

Charbonnier, C., Kolo, F. C., Duthon, V. B., Magnenat-Thalmann, N., Becker, C. D., Hoffmeyer, P., & Menetrey, J. (2011). Assessment of congruence and impingement of the hip joint in professional ballet dancers: A motion capture study. *Am J Sports Med, 39*(3), 557-566. doi:10.1177/0363546510386002

Charlton, P. C., Kenneally-Dabrowski, C., Sheppard, J., & Spratford, W. (2017). A simple method for quantifying jump loads in volleyball athletes. *J Sci Med Spor, 20*(3), 241-245. doi:10.1016/j.jsams.2016.07.007

Comin, J., Cook, J. L., Malliaras, P., McCormack, M., Calleja, M., Clarke, A., & Connell, D. (2013). The prevalence and clinical significance of sonographic tendon abnormalities in asymptomatic ballet dancers: A 24-month longitudinal study. *Br J Sports Med, 47*(2), 89-92. doi:10.1136/bjsports-2012-091303

Connaghan, D., Kelly, P., Connor, N. E. O., Gaffney, M., Walsh, M., & Mathuna, C. O. (2011, 28-31 Oct. 2011). *Multi-sensor classification of tennis strokes.* Paper presented at the SENSORS, 2011 IEEE.

Cook, J. L., & Docking, S. I. (2015). “Rehabilitation will increase the ‘capacity’ of your …insert musculoskeletal tissue here….” defining ‘tissue capacity’: A core concept for clinicians. *Br J Sports Med, 49*(23), 1484. doi:10.1136/bjsports-2015-094849

Costa, M. S., Ferreira, A. S., Orsini, M., Silva, E. B., & Felicio, L. R. (2016). Characteristics and prevalence of musculoskeletal injury in professional and non-professional ballet dancers. *Braz J Phys Ther, 20*(2), 166-175. doi:10.1590/bjpt-rbf.2014.0142

Cust, E. E., Sweeting, A. J., Ball, K., & Robertson, S. (2019). Machine and deep learning for sport-specific movement recognition: A systematic review of model development and performance. *J Sports Sci, 37*(5), 568-600. doi:10.1080/02640414.2018.1521769

Cust, E. E., Sweeting, A. J., Ball, K., & Robertson, S. (2021). Classification of australian football kick types in-situation via ankle-mounted inertial measurement units. *J Sports Sci, 39*(12), 1330-1338. doi:10.1080/02640414.2020.1868678

Demrozi, F., Pravadelli, G., Bihorac, A., & Rashidi, P. (2020). Human activity recognition using inertial, physiological and environmental sensors: A comprehensive survey. *IEEE Access, 8*, 210816-210836. doi:10.1109/ACCESS.2020.3037715

Devita, P., & Skelly, W. (1992). Effect of landing stiffness on joint kinetics and energetics in the lower extremity. *Med Sci Sports Exerc, 24*, 108-115.

Díaz, S., Stephenson, J. B., & Labrador, M. A. (2020). Use of wearable sensor technology in gait, balance, and range of motion analysis. *Appl Sci, 10*(1), 234. doi:https://doi.org/10.3390/app10010234

Diogo, M. A., Ribas, G. G., & Skare, T. L. (2016). Frequency of pain and eating disorders among professional and amateur dancers. *Sao Paulo Med J*, 0. doi:10.1590/1516-3180.2016.0077310516

Dore, B., & Guerra, R. (2007). Painful symptoms and associated factors in professional dancers. *Rev Bras Med Esporte, 13*(2), 67e-70e.

Dorschky, E., Nitschke, M., Martindale, C. F., van den Bogert, A. J., Koelewijn, A. D., & Eskofier, B. M. (2020). Cnn-based estimation of sagittal plane walking and running biomechanics from measured and simulated inertial sensor data. *Front Bioeng Biotechnol, 8*(604). doi:10.3389/fbioe.2020.00604

Dye, S. F. (2005). The pathophysiology of patellofemoral pain: A tissue homeostasis perspective. *Clin Orthop Relat Res*(436), 100-110. doi:10.1097/01.blo.0000172303.74414.7d

Ehara, Y., Fujimoto, H., Miyazaki, S., Mochimaru, M., Tanaka, S., & Yamamoto, S. (1997). Comparison of the performance of 3d camera systems. *Gait Posture, 5*, 251-255.

Ekegren, C. L., Quested, R., & Brodrick, A. (2014). Injuries in pre-professional ballet dancers: Incidence, characteristics and consequences. *J Sci Med Sport, 17*(3), 271-275. doi:10.1016/j.jsams.2013.07.013

Encarnacion, M., Meyers, M., Ruan, N., & Pease, D. (2000). Pain coping styles of ballet performers. *J Sport Behav, 23*(1), 21.

Feipel, V., Dalenne, S., Dugailly, P.-M., Salvia, P., & Rooze, M. (2004). Kinematics of the lumbar spine during classic ballet postures. *Med Probl Perform Art*(19), 174-180.

Fietzer, A. L., Chang, Y. J., & Kulig, K. (2012). Dancers with patellar tendinopathy exhibit higher vertical and braking ground reaction forces during landing. *J Sports Sci, 30*(11), 1157-1163. doi:10.1080/02640414.2012.695080

Fuller, M., Moyle, G. M., Hunt, A. P., & Minett, G. M. (2019). Ballet and contemporary dance injuries when transitioning to full-time training or professional level dance: A systematic review. *J Dance Med Sci, 23*(3), 112-125. doi:10.12678/1089-313x.23.3.112

Fuller, M., Moyle, G. M., & Minett, G. M. (2020). Injuries across a pre-professional ballet and contemporary dance tertiary training program: A retrospective cohort study. *J Sci Med Sport, 23*(12), 1166-1171. doi:10.1016/j.jsams.2020.06.012

Gabbett, T., Jenkins, D., & Abernethy, B. (2010). Physical collisions and injury during professional rugby league skills training. *J Sci Med Sport, 13*(6), 578-583. doi:10.1016/j.jsams.2010.03.007

Gabbett, T. J. (2013). Quantifying the physical demands of collision sports: Does microsensor technology measure what it claims to measure? *J Strength Cond Res, 27*(8), 2319-2322. doi:10.1519/JSC.0b013e318277fd21

Gabbett, T. J. (2016). The training-injury prevention paradox: Should athletes be training smarter and harder? *Br J Sports Med, 50*(5), 273-280. doi:10.1136/bjsports-2015-095788

Gabbett, T. J. (2020a). Debunking the myths about training load, injury and performance: Empirical evidence, hot topics and recommendations for practitioners. *Br J Sports Med, 54*(1), 58-66. doi:10.1136/bjsports-2018-099784

Gabbett, T. J. (2020b). How much? How fast? How soon? Three simple concepts for progressing training loads to minimize injury risk and enhance performance. *J Orthop Sports Phys Ther, 50*(10), 570-573. doi:10.2519/jospt.2020.9256

Gabbett, T. J., Hulin, B. T., Blanch, P., & Whiteley, R. (2016). High training workloads alone do not cause sports injuries: How you get there is the real issue. *Br J Sports Med, 50*(8), 444-445. doi:10.1136/bjsports-2015-095567

Gabbett, T. J., & Jenkins, D. G. (2011). Relationship between training load and injury in professional rugby league players. *J Sci Med Sport, 14*(3), 204-209. doi:10.1016/j.jsams.2010.12.002

Gabbett, T. J., Whyte, D. G., Hartwig, T. B., Wescombe, H., & Naughton, G. A. (2014). The relationship between workloads, physical performance, injury and illness in adolescent male football players. *Sports Med, 44*(7), 989-1003. doi:10.1007/s40279-014-0179-5

Gallo, T. F., Cormack, S. J., Gabbett, T. J., & Lorenzen, C. H. (2016). Pre-training perceived wellness impacts training output in australian football players. *J Sports Sci, 34*(15), 1445-1451. doi:10.1080/02640414.2015.1119295

Gamboa, J. M., Roberts, L. A., Maring, J., & Fergus, A. (2008). Injury patterns in elite preprofessional ballet dancers and the utility of screening programs to identify risk characteristics. *J Orthop Sports Phys Ther, 38*(3), 126-136. doi:10.2519/jospt.2008.2390

Gastin, P. B., McLean, O. C., Breed, R. V., & Spittle, M. (2014). Tackle and impact detection in elite australian football using wearable microsensor technology. *J Sports Sci, 32*(10), 947-953. doi:10.1080/02640414.2013.868920

Gastin, P. B., Meyer, D., & Robinson, D. (2013). Perceptions of wellness to monitor adaptive responses to training and competition in elite australian football. *J Strength Cond Res, 27*(9), 2518-2526. doi:10.1519/JSC.0b013e31827fd600

Gatchel, R. J., Peng, Y. B., Peters, M. L., Fuchs, P. N., & Turk, D. C. (2007). The biopsychosocial approach to chronic pain: Scientific advances and future directions. *Psychol Bull, 133*(4), 581-624. doi:10.1037/0033-2909.133.4.581

Gorwa, J., Dworak, L. B., Michnik, R., & Jurkojc, J. (2014). Kinematic analysis of modern dance movement "stag jump" within the context of impact loads, injury to the locomotor system and its prevention. *Med Sci Monit, 20*, 1082-1089. doi:10.12659/MSM.890126

Gorwa, J., Michnik, R. A., Nowakowska-Lipiec, K., Jurkojć, J., & Jochymczyk-Woźniak, K. (2019). Is it possible to reduce loads of the locomotor system during the landing phase of dance figures? Biomechanical analysis of the landing phase in grand jeté, entrelacé and ballonné. *Acta Bioeng Biomech, 21*(4), 111-121.

Groh, B. H., Fleckenstein, M., & Eskofier, B. M. (2016, 14-17 June 2016). *Wearable trick classification in freestyle snowboarding.* Paper presented at the 2016 IEEE 13th International Conference on Wearable and Implantable Body Sensor Networks (BSN).

Groh, Benjamin H., Fleckenstein, M., Kautz, T., & Eskofier, Bjoern M. (2017). Classification and visualization of skateboard tricks using wearable sensors. *Pervasive and Mobile Computing, 40*, 42-55. doi:https://doi.org/10.1016/j.pmcj.2017.05.007

Groh, Benjamin H., Kautz, T., & Schuldhaus, D. (2015). *Imu-based trick classification in skateboarding.* Paper presented at the KDD Workship on Large-Scale Sports Analytics.

Hainline, B., Turner, J. A., Caneiro, J. P., Stewart, M., & Lorimer Moseley, G. (2017). Pain in elite athletes—neurophysiological, biomechanical and psychosocial considerations: A narrative review. *Br J Sports Med, 51*(17), 1259. doi:10.1136/bjsports-2017-097890

Halson, S. L. (2014). Monitoring training load to understand fatigue in athletes. *Sports Med, 44 Suppl 2*, S139-147. doi:10.1007/s40279-014-0253-z

Hamilton, L., Hamilton, W., Warren, M., Keller, K., & Molnar, M. (1997). Factors contributing to the attrition rate in elite ballet students. *J Dance Med Sci, 1*(4), 131-138.

Han, S., Kim, R. S., Harris, J. D., & Noble, P. C. (2019). The envelope of active hip motion in different sporting, recreational, and daily-living activities: A systematic review. *Gait Posture, 71*, 227-233. doi:10.1016/j.gaitpost.2019.05.006

Harrison, C., & Ruddock-Hudson, M. (2017). Perceptions of pain, injury, and transition-retirement. The experiences of professional dancers. *J Dance Med Sci, 21*(2), 43-52.

Harwood, A., Campbell, A., Hendry, D., Ng, L., & Wild, C. Y. (2018). Differences in lower limb biomechanics between ballet dancers and non-dancers during functional landing tasks. *Phys Ther Sport, 32*, 180-186. doi:10.1016/j.ptsp.2018.05.005

Hendry, D., Campbell, A., Ng, L., Grisbrook, T. L., & Hopper, D. M. (2015). Effect of mulligan's and kinesio knee taping on adolescent ballet dancers knee and hip biomechanics during landing. *Scand J Med Sci Sports, 25*(6), 888-896. doi:10.1111/sms.12302

Hendry, D., Campbell, A., Ng, L., Harwood, A., & Wild, C. (2019). The difference in lower limb landing kinematics between adolescent dancers and non-dancers. *J Dance Med Sci, 23*(2), 72-79. doi:10.12678/1089-313x.23.2.72

Hendry, D., Chai, K., Campbell, A., Hopper, L., O'Sullivan, P., & Straker, L. (2020). Development of a human activity recognition system for ballet tasks. *Sports Med Open, 6*(1), 10. doi:10.1186/s40798-020-0237-5

Hendry, D., Leadbetter, R., McKee, K., Hopper, L., Wild, C., O'Sullivan, P., . . . Campbell, A. (2020). An exploration of machine-learning estimation of ground reaction force from wearable sensor data. *Sensors 20*(3). doi:10.3390/s20030740

Hendry, D., Napier, K., Hosking, R., Chai, K., Davey, P., Hopper, L., . . . Campbell, A. (2021). Development of a machine learning model for the estimation of hip and lumbar angles in ballet dancers. *Med Probl Perform Art, 36*(2), 61-71. doi:10.21091/mppa.2021.2009

Hendry, D., Straker, L., Campbell, A., Hopper, L., Tunks, R., & O'Sullivan, P. (2019). An exploration of pre-professional dancers' beliefs of the low back and dance-specific low back movements. *Med Probl Perform Art, 34*(3), 147-153. doi:10.21091/mppa.2019.3025

Henriksen, A., Mikalsen, M. H., Woldaregay, A. Z., Muzny, M., Hartvigsen, G., Hopstock, L. A., & Grimsgaard, S. (2018). Using fitness trackers and smartwatches to measure physical activity in research: Analysis of consumer wrist-worn wearables. *J Med Internet Res, 20*(3), e110. doi:10.2196/jmir.9157

Henriksen, M., Rosager, S., Aaboe, J., Graven-Nielsen, T., & Bliddal, H. (2011). Experimental knee pain reduces muscle strength. *J Pain, 12*(4), 460-467. doi:https://doi.org/10.1016/j.jpain.2010.10.004

Higgins, S., Higgins, L. Q., & Vallabhajosula, S. (2021). Site-specific concurrent validity of the actigraph gt9x link in the estimation of activity-related skeletal loading. *Med Sci Sports Exerc, 53*(5), 951-959. doi:10.1249/mss.0000000000002562

Hincapie, C. A., Morton, E. J., & Cassidy, J. D. (2008). Musculoskeletal injuries and pain in dancers: A systematic review. *Arch Phys Med Rehabil, 89*(9), 1819-1829. doi:10.1016/j.apmr.2008.02.020

Hjermstad, M. J., Fayers, P. M., Haugen, D. F., Caraceni, A., Hanks, G. W., Loge, J. H., . . . Kaasa, S. (2011). Studies comparing numerical rating scales, verbal rating scales, and visual analogue scales for assessment of pain intensity in adults: A systematic literature review. *J Pain Symptom Manage, 41*(6), 1073-1093. doi:10.1016/j.jpainsymman.2010.08.016

Hollaus, B., Stabinger, S., Mehrle, A., & Raschner, C. (2020). Using wearable sensors and a convolutional neural network for catch detection in american football. *Sensors (Basel), 20*(23). doi:10.3390/s20236722

Hulin, B. T., Gabbett, T. J., Johnston, R. D., & Jenkins, D. G. (2017). Wearable microtechnology can accurately identify collision events during professional rugby league match-play. *J Sci Med Sport*. doi:10.1016/j.jsams.2016.11.006

Jacobs, C. L., Cassidy, J. D., Cote, P., Boyle, E., Ramel, E., Ammendolia, C., . . . Schwartz, I. (2016). Musculoskeletal injury in professional dancers: Prevalence and associated factors: An international cross-sectional study. *Clin J Sport Med*. doi:10.1097/JSM.0000000000000314

Jacobs, C. L., Hincapie, C. A., & Cassidy, J. D. (2012). Musculoskeletal injuries and pain in dancers: A systematic review update. *J Dance Med Sci, 16*(2), 74-84.

Jang, J., Ankit, A., Kim, J., Jang, Y. J., Kim, H. Y., Kim, J. H., & Xiong, S. (2018). A unified deep-learning model for classifying the cross-country skiing techniques using wearable gyroscope sensors. *Sensors (Basel), 18*(11), 3819. doi:10.3390/s18113819

Jarvis, D. N., & Kulig, K. (2016). Lower extremity biomechanical demands during saut de chat leaps. *Med Probl Perform Art, 31*(4), 211-217. doi:10.21091/mppa.2016.4039

Jeffries, A. C., Wallace, L., & Coutts, A. J. (2016). Quantifying training loads in contemporary dance. *Int J Sports Physiol Perform*, 1-22. doi:10.1123/ijspp.2016-0159

Jeffries, A. C., Wallace, L., Coutts, A. J., Cohen, A. M., McCall, A., & Impellizzeri, F. M. (2020). Injury, illness, and training load in a professional contemporary dance company: A prospective study. *J Athl Train, 55*(9), 967-976. doi:10.4085/1062-6050-477-19

Jensen, U., Blank, P., Kugler, P., & Eskofier, B. M. (2016). Unobtrusive and energy-efficient swimming exercise tracking using on-node processing. *IEEE Sensors Journal, 16*(10), 3972-3980. doi:10.1109/JSEN.2016.2530019

Jensen, U., Prade, F., & Eskofier, B. M. (2013). *Classification of kinematic swimming data with emphasis on resource consumption.* Paper presented at the IEEE International Conference on Body Sensor Networks.

Jensen, U., Schmidt, M., Hennig, M., Dassler, F. A., Jaitner, T., & Eskofier, B. M. (2015). An imu-based mobile system for golf putt analysis. *Sports Eng, 18*(2), 123-133. doi:10.1007/s12283-015-0171-9

Jiao, L., Wu, H., Bie, R., Umek, A., & Kos, A. (2018). Multi-sensor golf swing classification using deep cnn. *Procedia Comput Sci, 129*, 59-65. doi:10.1016/j.procs.2018.03.046

Johnson, W., Mian, A., Robinson, M., Verheul, J., Lloyd, D., & Alderson, J. (2019). *Multidimensional ground reaction forces and moments from a single sacrum mounted accelerometer via deep learning.* Paper presented at the International Society of Biomechanics/ American Society of Biomechanics Calgary, Canada.

Johnson, W. R., Mian, A., Robinson, M. A., Verheul, J., Lloyd, D. G., & Alderson, J. A. (2021). Multidimensional ground reaction forces and moments from wearable sensor accelerations via deep learning. *IEEE Trans Biomed Eng, 68*(1), 289-297. doi:10.1109/TBME.2020.3006158

Jowitt, H. K., Durussel, J., Brandon, R., & King, M. (2020). Auto detecting deliveries in elite cricket fast bowlers using microsensors and machine learning. *J Sports Sci, 38*(7), 767-772. doi:10.1080/02640414.2020.1734308

Kautz, T. (2017). *Acquisition, filtering and analysis of positional and inertial data in sports*. Friedrich-Alexander-Universität Erlangen-Nürnberg.: FAU University Press.

Kautz, T., Groh, B. H., Hannink, J., Jensen, U., Strubberg, H., & Eskofier, B. M. (2017). Activity recognition in beach volleyball using a deep convolutional neural network. *Data Min Knowl Discov, 31*(6), 1678-1705. doi:10.1007/s10618-017-0495-0

Kelly, D., Coughlan, G. F., Green, B. S., & Caulfield, B. (2012). Automatic detection of collisions in elite level rugby union using a wearable sensing device. *Sports Eng, 15*(2), 81-92. doi:10.1007/s12283-012-0088-5

Kenny, S. J., Palacios-Derflingher, L., Whittaker, J. L., & Emery, C. A. (2018). The influence of injury definition on injury burden in preprofessional ballet and contemporary dancers. *J Orthop Sports Phys Ther, 48*(3), 185-193. doi:10.2519/jospt.2018.7542

Kenny, S. J., Whittaker, J. L., & Emery, C. A. (2016). Risk factors for musculoskeletal injury in preprofessional dancers: A systematic review. *Br J Sports Med, 50*(16), 997-1003. doi:10.1136/bjsports-2015-095121

Khan, K., Brown, J., Way, S., Vass, N., Crichton, K., Alexander, R., . . . Wark, J. (1995). Overuse injuries in classical ballet. *Sports Med, 19*(5), 341-357.

Kiernan, D., Hawkins, D. A., Manoukian, M. A. C., McKallip, M., Oelsner, L., Caskey, C. F., & Coolbaugh, C. L. (2018). Accelerometer-based prediction of running injury in national collegiate athletic association track athletes. *J Biomech, 73*, 201-209. doi:10.1016/j.jbiomech.2018.04.001

Kingma, D. P., & Ba, J. L. (2015). *Adam: A method for stachastic optimisation.* Paper presented at the International Conference on Learning Representations, San Diego, CA, USA.

Kjærgaard, M. B., Blunck, H., Godsk, T., Toftkjær, T., Christensen, D. L., & Grønbæk, K. (2010, 2010//). *Indoor positioning using gps revisited.* Paper presented at the Pervasive Computing, Berlin, Heidelberg.

Kobsar, D., Osis, S. T., Hettinga, B. A., & Ferber, R. (2014). Classification accuracy of a single tri-axial accelerometer for training background and experience level in runners. *J Biomech, 47*(10), 2508-2511. doi:https://doi.org/10.1016/j.jbiomech.2014.04.017

Kos, M., & Kramberger, I. (2017). A wearable device and system for movement and biometric data acquisition for sports applications. *IEEE Access, 5*, 6411-6420. doi:10.1109/ACCESS.2017.2675538

Kozai, A. C., Twitchett, E., Morgan, S., & Wyon, M. A. (2020). Workload intensity and rest periods in professional ballet: Connotations for injury. *Int J Sports Med, 41*(6), 373-379. doi:10.1055/a-1083-6539

Krasnow, D., Wilmerding, M. V., Stecyk, S., Wyon, M., & Koutedakis, Y. (2012). Examination of weight transfer strategies during the execution of grand battement devant at the barre, in the center, and traveling. *Med Probl Perform Art, 27*(2), 74-84.

Krawczyk, B. (2016). Learning from imbalanced data: Open challenges and future directions. *Prog Artif Intell, 5*(4), 221-232. doi:10.1007/s13748-016-0094-0

Kuhlman, N., & Min, C. H. (2021, 27-30 Jan. 2021). *Analysis and classification of basketball shooting form using wearable sensor systems.* Paper presented at the 2021 IEEE 11th Annual Computing and Communication Workshop and Conference (CCWC).

Kulig, K., Fietzer, A. L., & Popovich, J. M., Jr. (2011). Ground reaction forces and knee mechanics in the weight acceptance phase of a dance leap take-off and landing. *J Sports Sci, 29*(2), 125-131. doi:10.1080/02640414.2010.534807

Kulig, K., Loudon, J. K., Popovich, J. M., Jr., Pollard, C. D., & Winder, B. R. (2011). Dancers with achilles tendinopathy demonstrate altered lower extremity takeoff kinematics. *J Orthop Sports Phys Ther, 41*(8), 606-613. doi:10.2519/jospt.2011.3580

Kulig, K., Oki, K. C., Chang, Y. J., & Bashford, G. R. (2014). Achilles and patellar tendon morphology in dancers with and without tendon pain. *Med Probl Perform Art, 29*(4), 221-228.

Lampe, J., Borgetto, B., Groneberg, D. A., & Wanke, E. M. (2018). Prevalence, localization, perception and management of pain in dance: An overview. *Scand J Pain, 18*(4), 567-574. doi:10.1515/sjpain-2018-0105

Lara, O. D., & Labrador, M. A. (2013). A survey on human activity recognition using wearable sensors. *IEEE Communications Surveys & Tutorials, 15*(3), 1192-1209. doi:10.1109/SURV.2012.110112.00192

Leanderson, C., Leanderson, J., Wykman, A., Strender, L., Johansson, S., & Sundquist, K. (2011). Musculoskeletal injuries in young ballet dancers. *Knee Surg Sport Tr A, 19*(9), 1531-1535. doi:http://dx.doi.org/10.1007/s00167-011-1445-9

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature, 521*(7553), 436-444. doi:10.1038/nature14539

Lee, H.-H., Lin, C.-W., Wu, H.-W., Wu, T.-C., & Lin, C.-F. (2012). Changes in biomechanics and muscle activation in injured ballet dancers during a jump-land task with turnout (sissonne fermee). *J Sports Sci, 30*(7), 689-697.

Lee, L., Reid, D., Cadwell, J., & Palmer, P. (2017). Injury incidence, dance exposure and the use of the movement competency screen (msc) to identify variables associated with injury in full-time pre-professional dancers. *Int J Sports Phys Ther*, *12*(3), 352-370.

Leporace, G., Batista, L. A., Metsavaht, L., & Nadal, J. (2015, Aug). *Residual analysis of ground reaction forces simulation during gait using neural networks with different configurations.* Paper presented at the 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC).

Liederbach, M., Dilgen, F., & Rose, D. (2008). Incidence of anterior cruciate ligament injuries among elite ballet and modern dancers. *Am J Sports Med, 36*(9), 1779- 1788.

Liederbach, M., Hagins, M., Gamboa, J. M., & Welsh, T. M. (2012). Assessing and reporting dancer capacities, risk factors, and injuries: Recommendations from the iadms standard measures consensus initiative. *J Dance Med Sci, 16*(4), 139-153.

Liederbach, M., Kremenic, I. J., Orishimo, K. F., Pappas, E., & Hagins, M. (2014). Comparison of landing biomechanics between male and female dancers and athletes, part 2: Influence of fatigue and implications for anterior cruciate ligament injury. *Am J Sports Med, 42*(5), 1089-1095. doi:10.1177/0363546514524525

Liederbach, M., Richardson, M., Rodriguez, M., Compagno, J., Dilgen, F. E., & Rose, D. J. (2006). Jump exposures in the dance training environment: A measure of ergonomic demand. *J Athl Train, 41*, S85.

Liu, D.-X., Du, W., Wu, X., Wang, C., & Qiao, Y. (2016). *Deep rehabilitation gait learning for modeling knee joints of lower-limb exoskeleton.* Paper presented at the IEEE International Conference on Robotics and Biomimetics (ROBIO).

MacDonald, K., Bahr, R., Baltich, J., Whittaker, J. L., & Meeuwisse, W. H. (2017). Validation of an inertial measurement unit for the measurement of jump count and height. *Physical Therapy in Sport, 25*, 15-19. doi:https://doi.org/10.1016/j.ptsp.2016.12.001

Madgwick, S. O. H., Harrsion, A. J. L., & Vaidyanathan, R. (2011). *Estimation of imu and marg orientation using a gradient descent algorithm.* Paper presented at the 2011 IEEE International Conference on Rehabilitation Robotics, Zurich.

Mainwaring, L., Kerr, G., & Krasnow, D. (1993). Psychological correlates of dance injuries. *Med Probl Perform Art, 8*, 3-6.

Mainwaring, L. M., & Finney, C. (2017). Psychological risk factors and outcomes of dance injury: A systematic review. *J Dance Med Sci, 21*(3), 87-96. doi:10.12678/1089-313x.21.3.87

Mannini, A., & Sabatini, A. M. (2010). Machine learning methods for classifying human physical activity from on-body accelerometers. *Sensors (Basel), 10*(2), 1154-1175.

Mattiussi, A., Shaw, J. W., Brown, D. D., Price, P., Cohen, D. D., Pedlar, C. R., & Tallent, J. (2021). Jumping in ballet: A systematic review of kinetic and kinematic parameters. *Med Probl Perform Art, 36*(2), 108-128. doi:10.21091/mppa.2021.2011

Mattiussi, A. M., Shaw, J. W., Williams, S., Price, P. D., Brown, D. D., Cohen, D. D., . . . Tallent, J. (2021). Injury epidemiology in professional ballet: A five-season prospective study of 1596 medical attention injuries and 543 time-loss injuries. *Br J Sports Med*. doi:10.1136/bjsports-2020-103817

Mayes, S., Ferris, A. R., Smith, P., Garnham, A., & Cook, J. (2016a). Atraumatic tears of the ligamentum teres are more frequent in professional ballet dancers than a sporting population. *Skeletal Radiol, 45*(7), 959-967. doi:10.1007/s00256-016-2379-6

Mayes, S., Ferris, A. R., Smith, P., Garnham, A., & Cook, J. (2016b). Bony morphology of the hip in professional ballet dancers compared to athletes. *Eur Radiol*. doi:10.1007/s00330-016-4667-x

Mayes, S., Ferris, A. R., Smith, P., Garnham, A., & Cook, J. (2016c). Professional ballet dancers have a similar prevalence of articular cartilage defects compared to age- and sex-matched non-dancing athletes. *Clin Rheumatol, 35*(12), 3037-3043. doi:10.1007/s10067-016-3389-4

Mayes, S., Ferris, A. R., Smith, P., Garnham, A., & Cook, J. (2016d). Similar prevalence of acetabular labral tear in professional ballet dancers and sporting participants. *Clin J Sport Med, 26*(4), 307-313. doi:10.1097/jsm.0000000000000257

Mayes, S., Smith, P., & Cook, J. (2018). Impingement-type bony morphology was related to cartilage defects, but not pain in professional ballet dancers' hips. *J Sci Med Sport*. doi:10.1016/j.jsams.2018.02.014

McGrath, J. W., Neville, J., Stewart, T., & Cronin, J. (2019). Cricket fast bowling detection in a training setting using an inertial measurement unit and machine learning. *J Sports Sci, 37*(11), 1220-1226. doi:10.1080/02640414.2018.1553270

McNamara, D. J., Gabbett, T. J., Chapman, P., Naughton, G., & Farhart, P. (2015). The validity of microsensors to automatically detect bowling events and counts in cricket fast bowlers. *Int J Sports Physiol Perform, 10*(1), 71-75. doi:10.1123/ijspp.2014-0062

McPherson, A. M., Schrader, J. W., & Docherty, C. L. (2019). Ground reaction forces in ballet differences resulting from footwear and jump conditions. *J Dance Med Sci, 23*(1), 34-39. doi:10.12678/1089-313x.23.1.34

McVeigh, J. A., Winkler, E. A., Healy, G. N., Slater, J., Eastwood, P. R., & Straker, L. M. (2016). Validity of an automated algorithm to identify waking and in-bed wear time in hip-worn accelerometer data collected with a 24 h wear protocol in young adults. *Physiol Meas, 37*(10), 1636-1652. doi:10.1088/0967-3334/37/10/1636

Merriaux, P., Dupuis, Y., Boutteau, R., Vasseur, P., & Savatier, X. (2017). A study of vicon system positioning performance. *Sensors (Basel), 17*(7). doi:10.3390/s17071591

Mira, N. O., Marulanda, A. F. H., Pena, A. C. G., Torres, D. C., & Orrego, J. C. (2019). Study of ballet dancers during cou-de-pied derriere with demi-plie to pique arabesque. *J Dance Med Sci, 23*(4), 150-158. doi:10.12678/1089-313x.23.4.150

Mjosund, H. L., Boyle, E., Kjaer, P., Mieritz, R. M., Skallgard, T., & Kent, P. (2017). Clinically acceptable agreement between the vimove wireless motion sensor system and the vicon motion capture system when measuring lumbar region inclination motion in the sagittal and coronal planes. *BMC Musculoskelet Disord, 18*(1), 124. doi:10.1186/s12891-017-1489-1

Mundt, M., Koeppe, A., David, S., Witter, T., Bamer, F., Potthast, W., & Markert, B. (2020). Estimation of gait mechanics based on simulated and measured imu data using an artificial neural network. *Front Bioeng Biotechnol, 8*(41). doi:10.3389/fbioe.2020.00041

Murphy, M. C., Glasgow, P., & Mosler, A. B. (2021). Self-reported measures of training exposure: Can we trust them, and how do we select them? *Br J Sports Med*, bjsports-2021-104498. doi:10.1136/bjsports-2021-104498

Nagy, P., Brogden, C., Orr, G., & Greig, M. (2021). Within- and between-day loading response to ballet choreography. *Res Sports Med*, 1-12. doi:10.1080/15438627.2021.1929223

Negus, V., Hopper, D., & Briffa, N. K. (2005). Associations between turnout and lower extremity injuries in classical ballet dancers. *J Orthop Sports Phys Ther, 35*, 307-318.

Nicholas, P., Hefford, C., & Tumilty, S. (2012). The use of the patient-specific functional scale to measure rehabilitative progress in a physiotherapy setting. *J Man Manip Ther, 20*(3), 147-152. doi:10.1179/2042618612Y.0000000006

Novosel, B., Sekulic, D., Peric, M., Kondric, M., & Zaletel, P. (2019). Injury occurrence and return to dance in professional ballet: Prospective analysis of specific correlates. *Int J Environ Res Public Health, 16*(5). doi:10.3390/ijerph16050765

Ó Conaire, C., Connaghan, D., Kelly, P., O'Connor, N., Gaffney, M., & Buckley, J. (2010). *Combining inertial and visual sensing for human action recognition in tennis.* Paper presented at the International Multimedia Conference.

O'Reilly, M., Whelan, D., Chanialidis, C., Friel, N., Delahunt, E., Ward, T., & Caulfield, B. (2015, 9-12 June 2015). *Evaluating squat performance with a single inertial measurement unit.* Paper presented at the 2015 IEEE 12th International Conference on Wearable and Implantable Body Sensor Networks (BSN).

O'Reilly, M. A., Whelan, D. F., Ward, T. E., Delahunt, E., & Caulfield, B. (2017). Classification of lunge biomechanics with multiple and individual inertial measurement units. *Sports Biomech, 16*(3), 342-360. doi:10.1080/14763141.2017.1314544

O'Reilly, M. A., Whelan, D. F., Ward, T. E., Delahunt, E., & Caulfield, B. M. (2017). Classification of deadlift biomechanics with wearable inertial measurement units. *J Biomech, 58,* 155-161. doi:10.1016/j.jbiomech.2017.04.028

O'Sullivan, P., Caneiro, J. P., O'Keeffe, M., Smith, A., Dankaerts, W., Fersum, K., & O'Sullivan, K. (2018). Cognitive functional therapy: An integrated behavioral approach for the targeted management of disabling low back pain. *Phys Ther Sport, 98*(5), 408-423. doi:10.1093/ptj/pzy022

Orishimo, K., Kremenic, I., Pappas, E., Hagins, M., & Liederbach, M. (2009). Comparison of landing biomechanics between male and female professional dancers. *Am J Sports Med, 37,* 2187-2193.

Orishimo, K. F., Liederbach, M., Kremenic, I. J., Hagins, M., & Pappas, E. (2014). Comparison of landing biomechanics between male and female dancers and athletes, part 1: Influence of sex on risk of anterior cruciate ligament injury. *Am J Sports Med, 42*(5), 1082-1088. doi:10.1177/0363546514523928

Pappas, E., Sheikhzadeh, A., Hagins, M., & Nordin, M. (2007). The effect of gender and fatigue on the biomechanics of bilateral landings from a jump: Peak values. *J Sports Sci Med, 6*(1), 77-84.

Park, J., Kim, S. J., Na, Y., Kim, Y., & Kim, J. (2019). Development of a bendable outsole biaxial ground reaction force measurement system. *Sensors (Basel), 19*(11). doi:10.3390/s19112641

Peng, H. T., Chen, W. C., Kernozek, T. W., Kim, K., & Song, C. Y. (2015). Influences of patellofemoral pain and fatigue in female dancers during ballet jump-landing. *Int J Sports Med, 36*(9), 747-753. doi:10.1055/s-0035-1547220

Pernek, I., Kurillo, G., Stiglic, G., & Bajcsy, R. (2015). Recognizing the intensity of strength training exercises with wearable sensors. *J Biomed Inform, 58,* 145-155. doi:10.1016/j.jbi.2015.09.020

Phibbs, P. J., Roe, G., Jones, B., Read, D. B., Weakley, J., Darrall-Jones, J., & Till, K. (2017). Validity of daily and weekly self-reported training load measures in adolescent athletes. *J Strength Cond Res, 31*(4), 1121-1126. doi:10.1519/jsc.0000000000001708

Qaisar, S., Imtiaz, S., Glazier, P., Farooq, F., Jamal, A., Iqbal, W., & Lee, S. (2013). *A method for cricket bowling action classification and analysis using a system of inertial sensors.* Paper presented at the International Conference on Computational Science and its Applications Berlin, Heidelberg.

Rabe-Hesketh, S., & Skrondal, A. (2015). *Multilevel and longitudinal modelling using stata.* (Second ed.): College Station: Stata Press.

Ramel, E., Moritz, U., & Gun-Britt, J. (1999). Validation of a pain questionnaire (sefip) for dancers with a specially created test battery. *Med Probl Perform Art*, *14*, 196-203.

Rassem, A., El-Beltagy, M., & Saleh, M. (2017). *Cross-country skiing gears classification using deep learning*. ArXiv Preprint ArXiv:1706.08924.

Rindal, O. M. H., Seeberg, T. M., Tjønnås, J., Haugnes, P., & Sandbakk, Ø. (2017). Automatic classification of sub-techniques in classical cross-country skiing using a machine learning algorithm on micro-sensor data. *Sensors (Basel), 18*(1). doi:10.3390/s18010075

Rogalski, B., Dawson, B., Heasman, J., & Gabbett, T. J. (2013). Training and game loads and injury risk in elite australian footballers. *J Sci Med Sport, 16*(6), 499-503. doi:10.1016/j.jsams.2012.12.004

Salman, M., Qaisar, S., & Qamar, A. M. (2017). Classification and legality analysis of bowling action in the game of cricket. *Data Min Knowl Discov, 31*(6), 1706-1734. doi:10.1007/s10618-017-0511-4

Saw, A. E., Main, L. C., & Gastin, P. B. (2015). Monitoring athletes through self-report: Factors influencing implementation. *J Sports Sci Med, 14*(1), 137-146.

Schuldhaus, D., Zwick, C., Korger, H., Dorschky, E., Kirk, R., & Eskofier, B. M. (2015). *Inertial sensor-based approach for shot/pass classification during a soccer match*. Paper presented at the KDD Workshop on Large-Scale Sports Analytics, Sydney, Australia.

Shahabpoor, E., Pavic, A., Brownjohn, J. M. W., Billings, S. A., Guo, L. Z., & Bocian, M. (2018). Real-life measurement of tri-axial walking ground reaction forces using optimal network of wearable inertial measurement units. *IEEE Trans Neural Syst Rehabil Eng, 26*(6), 1243-1253. doi:10.1109/tnsre.2018.2830976

Shahar, N., Ghazali, N. F., As'ari, M. A., & Swee, T. T. (2020). Wearable inertial sensor for human activity recognition in field hockey: Influence of sensor combination and sensor location. *J. Phys.: Conf. Ser, 1529*, 22015. doi:10.1088/1742-6596/1529/2/022015

Shaw, J. W., Mattiussi, A. M., Brown, D. D., Williams, S., Kelly, S., Springham, M., . . . Tallent, J. (2021). Dance exposure, individual characteristics, and injury risk over five seasons in a professional ballet company. *Med Sci Sports Exerc, Publish Ahead of Print*. doi:10.1249/MSS.0000000000002725

Sinclair, J., Richards, J., Taylor, P. J., Edmundson, C. J., Brooks, D., & Hobbs, S. J. (2013). Three-dimensional kinematic comparison of treadmill and overground running. *Sports Biomech, 12*(3), 272-282. doi:10.1080/14763141.2012.759614

Skazalski, C., Whiteley, R., Hansen, C., & Bahr, R. (2018). A valid and reliable method to measure jump-specific training and competition load in elite volleyball players. *Scand J Med Sci Sports, 28*(5), 1578-1585. doi:10.1111/sms.13052

Slater, A., Campbell, A., Smith, A., & Straker, L. (2015). Greater lower limb flexion in gymnastic landings is associated with reduced landing force: A repeated measures study. *Sports Biomech, 14*(1), 45-56. doi:10.1080/14763141.2015.1029514

Smith, P. J., Gerrie, B. J., Varner, K. E., McCulloch, P. C., Lintner, D. M., & Harris, J. D. (2015). Incidence and prevalence of musculoskeletal injury in ballet: A systematic review. *Orthop J Sports Med, 3*(7), 2325967115592621. doi:10.1177/2325967115592621

Smith, T. O., Davies, L., de Medici, A., Hakim, A., Haddad, F., & Macgregor, A. (2016). Prevalence and profile of musculoskeletal injuries in ballet dancers: A systematic review and meta-analysis. *Phys Ther Sport, 19*, 50-56. doi:https://doi.org/10.1016/j.ptsp.2015.12.007

Srivastava, R., Patwari, A., Kumar, S., Mishra, G., Kaligounder, L., & Sinha, P. (2015, 1-4 Nov. 2015). *Efficient characterization of tennis shots and game analysis using wearable sensors data.* Paper presented at the 2015 IEEE SENSORS.

Stetter, B. J., Ringhof, S., Krafft, F. C., Sell, S., & Stein, T. (2019). Estimation of knee joint forces in sport movements using wearable sensors and machine learning. *Sensors (Basel), 19*(17). doi:10.3390/s19173690

Stoeve, M., Schuldhaus, D., Gamp, A., Zwick, C., & Eskofier, B. M. (2021). From the laboratory to the field: Imu-based shot and pass detection in football training and game scenarios using deep learning. *Sensors (Basel), 21*(9). doi:10.3390/s21093071

Suri, P., Boyko, E. J., Goldberg, J., Forsberg, C. W., & Jarvik, J. G. (2014). Longitudinal associations between incident lumbar spine mri findings and chronic low back pain or radicular symptoms: Retrospective analysis of data from the longitudinal assessment of imaging and disability of the back (laidback). *BMC Musculoskelet Disord, 15*(1), 152. doi:10.1186/1471-2474-15-152

Swain, C. T. V., Bradshaw, E. J., Whyte, D. G., & Ekegren, C. L. (2017). Life history and point prevalence of low back pain in pre-professional and professional dancers. *Phys Ther Sport*. doi:10.1016/j.ptsp.2017.01.005

Swain, C. T. V., Bradshaw, E. J., Whyte, D. G., & Ekegren, C. L. (2018). The prevalence and impact of low back pain in pre-professional and professional dancers: A prospective study. *Phys Ther Sport, 30*, 8-13. doi:10.1016/j.ptsp.2017.10.006

Taghavi, S., Davari, F., Malazi, H. T., & Abin, A. A. (2019, 24-25 Oct. 2019). *Tennis stroke detection using inertial data of a smartwatch.* Paper presented at the 2019 9th International Conference on Computer and Knowledge Engineering (ICCKE).

Tajet-Foxell, B., & Rose, F. D. (1995). Pain and pain tolerance in professional ballet dancers. *British Journal of Sports Medicine, 29*(1), 31.

Tan, T., Chiasson, D. P., Hu, H., & Shull, P. B. (2019). Influence of imu position and orientation placement errors on ground reaction force estimation. *J Biomech, 97*, 109416. doi:10.1016/j.jbiomech.2019.109416

Teufl, W., Miezal, M., Taetz, B., Frohlich, M., & Bleser, G. (2019). Validity of inertial sensor based 3d joint kinematics of static and dynamic sport and physiotherapy specific movements. *PLoS One, 14*(2), e0213064. doi:10.1371/journal.pone.0213064

Thomas, H., & Tarr, J. (2009). Dancers' perceptions of pain and injury: Positive and negative effects. *J Dance Med Sci, 13*(2), 51-59.

Trentacosta, N., Sugimoto, D., & Micheli, L. J. (2017). Hip and groin injuries in dancers: A systematic review. *Sports Health, 9*(5), 422-427. doi:10.1177/1941738117724159

Trost, S. G., Zheng, Y., & Wong, W.-K. (2014). Machine learning for activity recognition: Hip versus wrist data. *Physiol Meas, 35*(11), 2183.

Twitchett, E., Angioi, M., Koutedakis, Y., & Wyon, M. (2010). The demands of a working day among female professional ballet dancers. *J Dance Med Sci, 14*(4), 127-132.

van Winden, D., Van Rijn, R. M., Richardson, A., Savelsbergh, G. J. P., Oudejans, R. R. D., & Stubbe, J. H. (2019). Detailed injury epidemiology in contemporary dance: A 1-year prospective study of 134 students. *BMJ Open Sport Exerc Med, 5*(1), e000453. doi:10.1136/bmjsem-2018-000453

Vassallo, A. J., Hillier, C. E., Pappas, E., & Stamatakis, E. (2017). *Safe dance report iv: Investigating injuries in asutralian professional dancer*. Retrieved from Canberra, Australia:

Vitali, R. V., McGinnis, R. S., & Perkins, N. C. (2020). Robust error-state kalman filter for estimating imu orientation. *IEEE Sensors Journal*, 1-1. doi:10.1109/JSEN.2020.3026895

Volkova, V., & Kenny, S. J. (2020). 153 musculoskeletal injuries and dance exposure across three years in elite adolescent ballet dancers: Is there a pattern? *Br J Sports Med, 54*(Suppl 1), A65. doi:http://dx.doi.org/10.1136/bjsports-2020-IOCAbstracts.153

Wang, T. J., & Russell, J. A. (2018). A tenuous pas de deux: Examining university dancers' access to and satisfaction with healthcare delivery. *Med Probl Perform Art, 33*(2), 111-117. doi:10.21091/mppa.2018.2018

Whiteside, D., Cant, O., Connolly, M., & Reid, M. (2017). Monitoring hitting load in tennis using inertial sensors and machine learning. *Int J Sports Physiol Perform*, 1-20. doi:10.1123/ijspp.2016-0683

Willmott, C. J., & Matsuura, K. (2005). Advantages of the mean absolute error (mae) over the root mean square error (rmse) in assessing average model performance. *Clim Res, 30*(1), 79-82. doi:10.3354/cr030079

Winston, P., Awan, R., Cassidy, J. D., & Bleakney, R. K. (2007). Clinical examination and ultrasound of self-reported snapping hip syndrome in elite ballet dancers. *Am J Sports Med, 35*(1), 118-126. doi:10.1177/0363546506293703

Wouda, F. J., Giuberti, M., Bellusci, G., Maartens, E., Reenalda, J., van Beijnum, B. F., & Veltink, P. H. (2018). Estimation of vertical ground reaction forces and sagittal knee kinematics during running using three inertial sensors. *Front Physiol, 9*, 218. doi:10.3389/fphys.2018.00218

Wundersitz, D. W., Josman, C., Gupta, R., Netto, K. J., Gastin, P. B., & Robertson, S. (2015). Classification of team sport activities using a single wearable tracking device. *J Biomech, 48*(15), 3975-3981. doi:10.1016/j.jbiomech.2015.09.015

Wyon, M. A., Twitchett, E., Angioi, M., Clarke, F., Metsios, G., & Koutedakis, Y. (2011). Time motion and video analysis of classical ballet and contemporary dance performance. *Int J Sports Med, 32*(11), 851-855. doi:10.1055/s-0031-1279718

Xia, K., Wang, H., Xu, M., Li, Z., He, S., & Tang, Y. (2020). Racquet sports recognition using a hybrid clustering model learned from integrated wearable sensor. *Sensors (Basel), 20*(6), 1638. doi:10.3390/s20061638

Zhang, H., Fu, Z., & Shu, K. (2019). Recognizing ping-pong motions using inertial data based on machine learning classification algorithms. *IEEE Access, 7*, 167055-167064. doi:10.1109/ACCESS.2019.2953772

APPENDICES

Appendix A
Study 1 and 2: Ethics Approval

Curtin University

Office of Research and Development

GPO Box U1987
Perth Western Australia 6845

Telephone +61 8 9266 7863
Facsimile +61 8 9266 3793
Web research.curtin.edu.au

06-Apr-2017

Name: Leon Straker
Department/School: School of Physiotherapy and Exercise Science
Email: L.Straker@curtin.edu.au

Dear Leon Straker

RE: Ethics approval
Approval number: HRE2017-0185

Thank you for submitting your application to the Human Research Ethics Office for the project **Commercial wearable sensors for movement identification and characterization; a validation in ballet dancers**.

Your application was reviewed through the Curtin University low risk ethics review process.

The review outcome is: **Approved.**

Your proposal meets the requirements described in National Health and Medical Research Council's (NHMRC) *National Statement on Ethical Conduct in Human Research (2007).*

Approval is granted for a period of one year from **06-Apr-2017** to **05-Apr-2018**. Continuation of approval will be granted on an annual basis following submission of an annual report.

Personnel authorised to work on this project:

Name	Role
Straker, Leon	CI
Hendry, Danica	Student
Campbell, Amity	Supervisor
O'Sullivan, Peter	Supervisor

Standard conditions of approval

1. Research must be conducted according to the approved proposal
2. Report in a timely manner anything that might warrant review of ethical approval of the project including:
    - proposed changes to the approved proposal or conduct of the study

- unanticipated problems that might affect continued ethical acceptability of the project
- major deviations from the approved proposal and/or regulatory guidelines
- serious adverse events

3. Amendments to the proposal must be approved by the Human Research Ethics Office before they are implemented (except where an amendment is undertaken to eliminate an immediate risk to participants)
4. An annual progress report must be submitted to the Human Research Ethics Office on or before the anniversary of approval and a completion report submitted on completion of the project
5. Personnel working on this project must be adequately qualified by education, training and experience for their role, or supervised
6. Personnel must disclose any actual or potential conflicts of interest, including any financial or other interest or affiliation, that bears on this project
7. Changes to personnel working on this project must be reported to the Human Research Ethics Office
8. Data and primary materials must be retained and stored in accordance with the Western Australian University Sector Disposal Authority (WAUSDA) and the Curtin University Research Data and Primary Materials policy
9. Where practicable, results of the research should be made available to the research participants in a timely and clear manner
10. Unless prohibited by contractual obligations, results of the research should be disseminated in a manner that will allow public scrutiny; the Human Research Ethics Office must be informed of any constraints on publication
11. Ethics approval is dependent upon ongoing compliance of the research with the Australian Code for the Responsible Conduct of Research, the National Statement on Ethical Conduct in Human Research, applicable legal requirements, and with Curtin University policies, procedures and governance requirements
12. The Human Research Ethics Office may conduct audits on a portion of approved projects.

Special Conditions of Approval

Please include the first sentence of HREC statement in the Info session and Social media recruitment material.

This letter constitutes ethical approval only. This project may not proceed until you have met all of the Curtin University research governance requirements.

Should you have any queries regarding consideration of your project, please contact the Ethics Support Officer for your faculty or the Ethics Office at hrec@curtin.edu.au or on 9266 2784.

Yours sincerely

Signature Redacted

Dr Catherine Gangell
Manager, Research Integrity

Appendix B

Study 1: Participant Recruitment Materials

Information Session Outline

- Explain where the researchers are from and that this is part of a PhD student project- *have participant information sheets being passed around*
- Brief background on what the research study is about
    - The large physical workloads that dancers undertake can result in fatigue which can lead to the development of pain and impact performance
    - Researchers are looking at ways to track how often dance movements are performed and measure characteristics of the movements (e.g. how high you jump)
    - Small wearable sensor may be able to be used to collect this information (show Actigraph Link to dancers) however as yet they have not yet been widely used within dance
- We are looking for pre-professional and professional female dancers aged between 18 and 30 to take part in this project to help us "teach" these sensors how to recognise dance movements
- Participation in this study is optional. If you do not want to participate in the study it will not affect your further training or your position in the course
- What testing will involve:
    - Sign an informed consent sheet which will include and optional consent for the data we collect to be used in future studies
    - Attend a single (approximately 30 minute) data collection session in one of the dance studios at WAAPA. There will be around 4-6 participants at each data collection and you will be performing tasks together
    - Height and weight will be measured
    - You will then have 8 of these (*demonstrate*) small sensors attached to you using low allergenic tape- upper back, lower back, both thighs, both shins and both wrists. So we can easily secure them to your body we ask that you wear shorts and a crop top. *Researcher to demonstrate on own leg how the sensor will be taped on.*
    - All the movements you perform will be movements you commonly do in your normal ballet class:
        - You will be asked to perform a series of discrete tasks specific to ballet- these will be jumping tasks, turning tasks and tasks where you lift your leg
        - You will then be taught 2x 2 minute choreographed phrases that will incorporate the discrete movements
    - At the end we will ask you to complete a short survey on your thoughts about wearing the sensors
    - We anticipate that data collection will take 40 minutes to complete
- By taking part in this study you will be assisting in the development of technology which can be used in the future to collect data in a normal dance class setting which allows us to find out more about the specific components that may contribute to pain and injury in dancers.
- All of your data will be kept confidential and you will be identified by a participant number. The research team will be the only people who will be able to identify you. The data will be kept in a locked cabinet and a password protected computer drive for 7 years.
- The results of this study will be published in scientific journals and presented at scientific conferences. The system we develop will be used in future research examining performance, injury and pain
- If you are interested in being involved, please come and talk to us now or contact us on the number provided.
- Remind students that participation is optional.

Appendix C
Study 1: Participant Information and Consent Form

Curtin University

Participant Information Sheet

HREC Project Number:	
Project Title:	*Commercial wearable sensors for movement identification and characterization; a validation in ballet dancers. Part A*
Principal Investigator:	*Prof Leon Straker*
Co-investigators:	*Danica Hendry* *Dr Amity Campbell* *Prof Peter O'Sullivan* *Dr Luke Hopper*
Version Number:	*2*
Version Date:	*3rd April, 2017*

Invitation statement
This is an invitation to participate in a research study which is part of a student PhD project. Please take your time to read and understand the following information about why the study is being conducted and what it will involve. Do not hesitate to ask us if you need any clarification or if you would like more details. This information sheet will help you decide whether or not to take part in the study.

What is the research study about?
Dancing requires a large physical work load that we know results in large forces on the body. This has been associated with the development of fatigue which can contribute towards poor performance as well as injury and pain. As a result, researchers are looking at ways to track how often particular dance movements are performed (eg how many jumps you have performed) and measure the characteristics of these movements (eg how high did you jump). This information will help a better understanding of the relationships between work load, fatigue, performance injury and pain. Recently available small wearable sensors may be able to measure dance movements accurately during normal dance training.

To utilize these wearable sensors in measuring the physical work load of dancers we need to "teach" a computer what the key movements within dance are. This is called machine learning. This has started to be done in sports such as tennis, rugby and soccer. However within dance wearable sensors have only been used at a very basic level. The current study will aim to develop a wearable sensor system using machine learning to identify common movements in classical ballet. The findings of this study will allow for future field based collection of physical work load to be used in dance research related to musculoskeletal injury/pain and performance

Why am I being asked to take part?
We are recruiting pre-professional and professional female dancers aged between 18 and 30 to take part in this project.

Curtin University Human Research Ethics Committee (HREC) has approved this study (HREC number XX/XXXX)

Curtin University

Do I have to take part in this research study?
Participation in this study is optional. Once you have read this information sheet we are happy to answer any questions you may have. It is then your decision whether or not to volunteer for this project. If you do decide to volunteer, you will then be asked to consent to participate in the study. Following this, you are free to withdraw from the data collection at any time. Your participation in this project will not influence your position in your course of study. There will also be an optional consent for you to sign in relation to future use of the data for related research projects.

What will I have to do if I take part?
If you agree to take part in this study, you will be asked to attend a single data collection session in a dance studio at your dance school/ company studio. We will ask you to wear a crop top and fitted shorts and have a pair of your normal pointe shoes and ballet flats or demi pointes with you.

We will measure your height and your weight. You will then have 8 small sensors (about the size of 50 cent coin) secured to your upper back, lower back, both thighs, both shins and both wrists using low allergenic tape. You will be given time to warm up and familiarize yourself with wearing the sensors. Then we will ask you to perform a series of discrete movements that are commonly performed within classical ballet, these will include turns, jumps and techniques which involve lifting your leg (for example arabesque and develloppe to second position). You will be asked to perform each movement three times, and for movements which are performed on one leg or towards one direction, we will ask you to perform it on both sides. Following the discrete movement tasks you will be taught two short (approximately 2 minutes) movement phrases which will incoroporate the movements you performed previously. You will be asked to perform these twice. A video camera will also be used throughout data collection for data processing purposes.

At the end of the movements we will ask you to complete a one page survey on your thoughts about wearing the sensors.

We anticipate the data collection will take 40 minutes to complete (10 minutes set up time and 30 minutes movement time). Data collection will be done in a group of 4-6 people, and all tasks will be peformed as a group.

What are the possible risks, inconveniences and any discomfort?
There may be some discomfort when removing the sensors, as the adhesive is similar to a first-aid plaster. You may feel a bit fatigued at the end of the data collection, although the physical requirements are less than those you would do in a typical dance class.

What are the possible benefits of taking part?
If you take part in this study, you will be exposed to technology that is used within the professional sporting arena to measure physical workload and may become common in dance companies in the future. The outcomes of this study will allow for specific formulas to be developed which will allow for this technology to be utilized in dance research and within dance practice You will also gain insight into the data collection process for a dance related science project which will assist you in broadening your understanding of the different fields and career pathways within dance.

Will my data be kept confidential?
When you attend data collection you will be given a participant number. The researchers will have a record of your number but data recorded will use this number, not your name. Your data will thus be de-identified from the time of data collection. Your results will not be identifiable as belonging to you by anyone other than the research team. All electronic data will be stored on a

password protected computer drive which only the research team will be able to access. All physical data (such as questionairres) will be kept in a locked cabinet located within a secure office in the School of Physiotherapy and Exercise Science at Curtin University. All data will be kept for 7 years.

What will happen to the results of the research study?
The results of this study will be published in one or more scientific journals and presented at scientific conferences. The system developed in this study will be utilized in future research examining performance, injury, pain and wellness in dancers.

What happens next and who can I contact about the research?
If you would like to know more at any stage, please feel free to contact Danica Hendry, who will be happy to discuss this information with you further and answer any questions you may have. Danica's contact details are:
Tel: 0421556854 or email: danica.hendry@postgrad.curtin.edu.au.

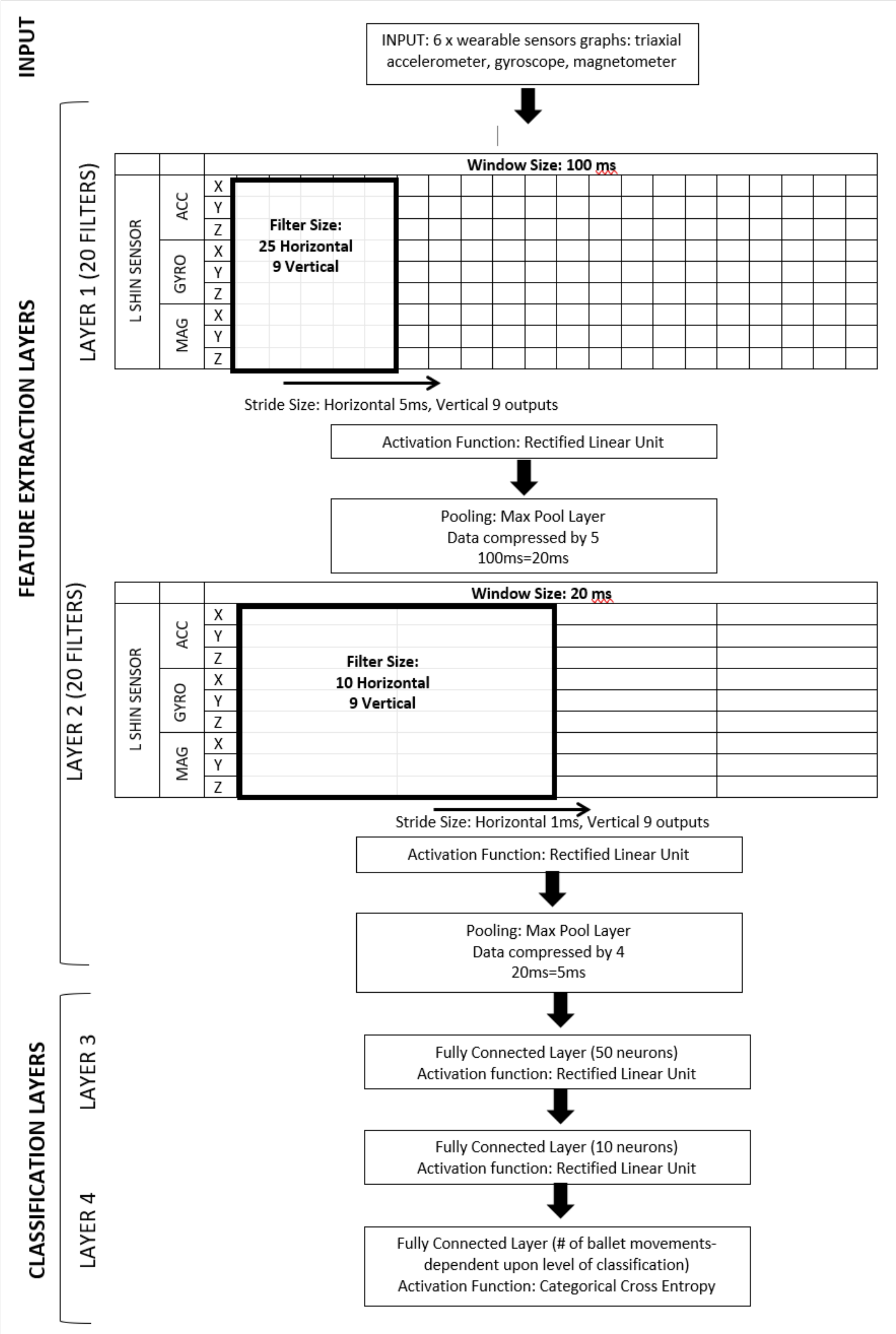
If you decide to take part in this research we will ask you to sign the consent form. By signing it is telling us that you understand what you have read and what has been discussed Please take your time and ask any questions you have before you decide what to do. You will be given a copy of this information and the consent form to keep.

Thank you for considering participating in this study.

Curtin University Human Research Ethics Committee (HREC) has approved this study (HREC number **HRE2017-0185**). Should you wish to discuss the study with someone not directly involved, in particular, any matters concerning the conduct of the study or your rights as a participant, or you wish to make a confidential complaint, you may contact the Ethics Officer on (08) 9266 9223 or the Manager, Research Integrity on (08) 9266 7093 or email hrec@curtin.edu.au.

Appendix D

Study 1: Supplementary Digital Content Machine Learning Model Architecture



Definition of terms:

Stride	The size of the step that the filter takes in the convolution layer
Rectified Linear Unit	A non-linear activation function to transform input values = max(0, x)
Pooling and Max Pool Layer	A function that reduces the spatial representation (size) of the data in a neural network. This helps reduce the number of parameters and computation in addition to reducing overfitting when training the network.
Neuron	A mathematical approximation of a biological neuron. It takes a vector of inputs, performs a transformation, and outputs a single scalar value.
Fully Connected Layer	Neurons in a fully connected layer have neurons (nodes) connected to all activations in the previous layer.
Categorical Cross Entropy	A loss (error) function used to evaluate how well a model performs on a multi-class classification task.

Appendix E
Study 2: Recruitment Flier

Curtin University

Commercial wearable sensors for movement identification and characterization;

a validation in ballet dancers

DANCE RESEARCH VOLUNTEERS NEEDED!

We are seeking **pre-professional and professional 16-30 year old female dancers** to help us develop a wearable movement sensor set to analyse ballet movements.

You will be required to participate in **a single 50 minute data collection session at Curtin University** where you will **perform a series of commonly practiced dance movements** while wearing a wearable sensor set in a motion analysis laboratory.

Participation in this project will provide you with valuable insight into the diverse world of dance science.

For further information please contact Danica Hendry

danica.hendry@postgrad.curtin.edu.au

Curtin University Human Research Ethics Committee (HREC) has approved this study (HREC number HRE2017-0185).

Appendix F
Study 2: Participant Information and Consent Form

Curtin University

Participant Information Sheet

HREC Project Number:	
Project Title:	*Commercial wearable sensors for movement identification and characterization; a validation in ballet dancers. Part A*
Principal Investigator:	*Prof Leon Straker*
Co-investigators:	*Danica Hendry* *Dr Amity Campbell* *Prof Peter O'Sullivan* *Dr Luke Hopper*
Version Number:	*2*
Version Date:	*3rd April, 2017*

Invitation statement
This is an invitation to participate in a research study which is part of a student PhD project. Please take your time to read and understand the following information about why the study is being conducted and what it will involve. Do not hesitate to ask us if you need any clarification or if you would like more details. This information sheet will help you decide whether or not to take part in the study.

What is the research study about?
Dancing requires a large physical work load that we know results in large forces on the body. This has been associated with the development of fatigue which can contribute towards poor performance as well as injury and pain. As a result, researchers are looking at ways to track how often particular dance movements are performed (eg how many jumps you have performed) and measure the characteristics of these movements (eg how high did you jump). This information will help a better understanding of the relationships between work load, fatigue, performance injury and pain. Recently available small wearable sensors may be able to measure dance movements accurately during normal dance training.

To utilize these wearable sensors in measuring the physical work load of dancers we need to "teach" a computer what the key movements within dance are. This is called machine learning. This has started to be done in sports such as tennis, rugby and soccer. However within dance wearable sensors have only been used at a very basic level. The current study will aim to develop a wearable sensor system using machine learning to identify common movements in classical ballet. The findings of this study will allow for future field based collection of physical work load to be used in dance research related to musculoskeletal injury/pain and performance

Why am I being asked to take part?
We are recruiting pre-professional and professional female dancers aged between 18 and 30 to take part in this project.

Curtin University Human Research Ethics Committee (HREC) has approved this study (HREC number XX/XXXX)

Curtin University

Do I have to take part in this research study?
Participation in this study is optional. Once you have read this information sheet we are happy to answer any questions you may have. It is then your decision whether or not to volunteer for this project. If you do decide to volunteer, you will then be asked to consent to participate in the study. Following this, you are free to withdraw from the data collection at any time. Your participation in this project will not influence your position in your course of study. There will also be an optional consent for you to sign in relation to future use of the data for related research projects.

What will I have to do if I take part?
If you agree to take part in this study, you will be asked to attend a single data collection session in a dance studio at your dance school/ company studio. We will ask you to wear a crop top and fitted shorts and have a pair of your normal pointe shoes and ballet flats or demi pointes with you.

We will measure your height and your weight. You will then have 8 small sensors (about the size of 50 cent coin) secured to your upper back, lower back, both thighs, both shins and both wrists using low allergenic tape. You will be given time to warm up and familiarize yourself with wearing the sensors. Then we will ask you to perform a series of discrete movements that are commonly performed within classical ballet, these will include turns, jumps and techniques which involve lifting your leg (for example arabesque and develloppe to second position). You will be asked to perform each movement three times, and for movements which are performed on one leg or towards one direction, we will ask you to perform it on both sides. Following the discrete movement tasks you will be taught two short (approximately 2 minutes) movement phrases which will incoroporate the movements you performed previously. You will be asked to perform these twice. A video camera will also be used throughout data collection for data processing purposes.

At the end of the movements we will ask you to complete a one page survey on your thoughts about wearing the sensors.

We anticipate the data collection will take 40 minutes to complete (10 minutes set up time and 30 minutes movement time). Data collection will be done in a group of 4-6 people, and all tasks will be peformed as a group.

What are the possible risks, inconveniences and any discomfort?
There may be some discomfort when removing the sensors, as the adhesive is similar to a first-aid plaster. You may feel a bit fatigued at the end of the data collection, although the physical requirements are less than those you would do in a typical dance class.

What are the possible benefits of taking part?
If you take part in this study, you will be exposed to technology that is used within the professional sporting arena to measure physical workload and may become common in dance companies in the future. The outcomes of this study will allow for specific formulas to be developed which will allow for this technology to be utilized in dance research and within dance practice You will also gain insight into the data collection process for a dance related science project which will assist you in broadening your understanding of the different fields and career pathways within dance.

Will my data be kept confidential?
When you attend data collection you will be given a participant number. The researchers will have a record of your number but data recorded will use this number, not your name. Your data will thus be de-identified from the time of data collection. Your results will not be identifiable as belonging to you by anyone other than the research team. All electronic data will be stored on a

Curtin University

password protected computer drive which only the research team will be able to access. All physical data (such as questionairres) will be kept in a locked cabinet located within a secure office in the School of Physiotherapy and Exercise Science at Curtin University. All data will be kept for 7 years.

What will happen to the results of the research study?
The results of this study will be published in one or more scientific journals and presented at scientific conferences. The system developed in this study will be utilized in future research examining performance, injury, pain and wellness in dancers.

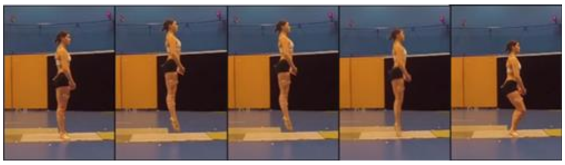
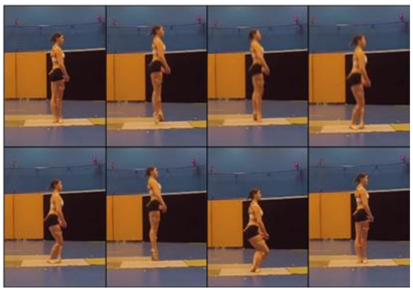
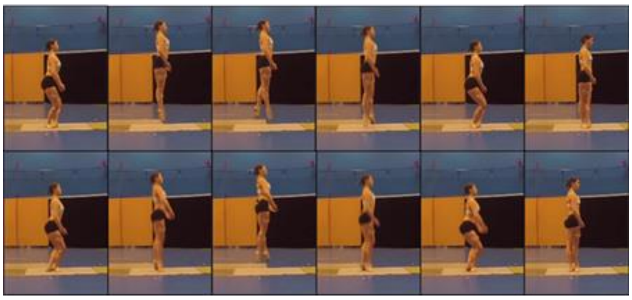
What happens next and who can I contact about the research?
If you would like to know more at any stage, please feel free to contact Danica Hendry, who will be happy to discuss this information with you further and answer any questions you may have. Danica's contact details are:
Tel: 0421556854 or email: danica.hendry@postgrad.curtin.edu.au.

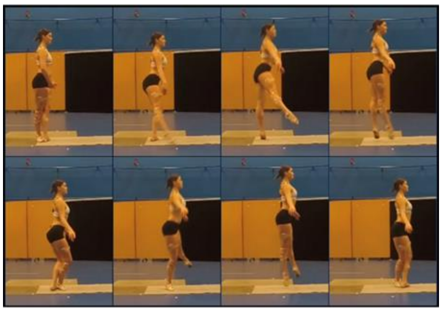
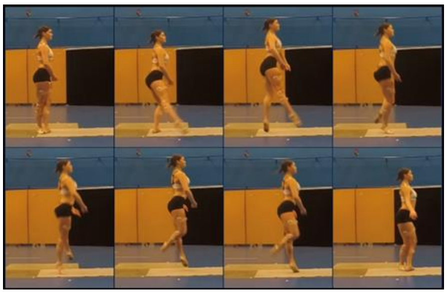
If you decide to take part in this research we will ask you to sign the consent form. By signing it is telling us that you understand what you have read and what has been discussed Please take your time and ask any questions you have before you decide what to do. You will be given a copy of this information and the consent form to keep.

Thank you for considering participating in this study.

Curtin University Human Research Ethics Committee (HREC) has approved this study (HREC number **HRE2017-0185**). Should you wish to discuss the study with someone not directly involved, in particular, any matters concerning the conduct of the study or your rights as a participant, or you wish to make a confidential complaint, you may contact the Ethics Officer on (08) 9266 9223 or the Manager, Research Integrity on (08) 9266 7093 or email hrec@curtin.edu.au.

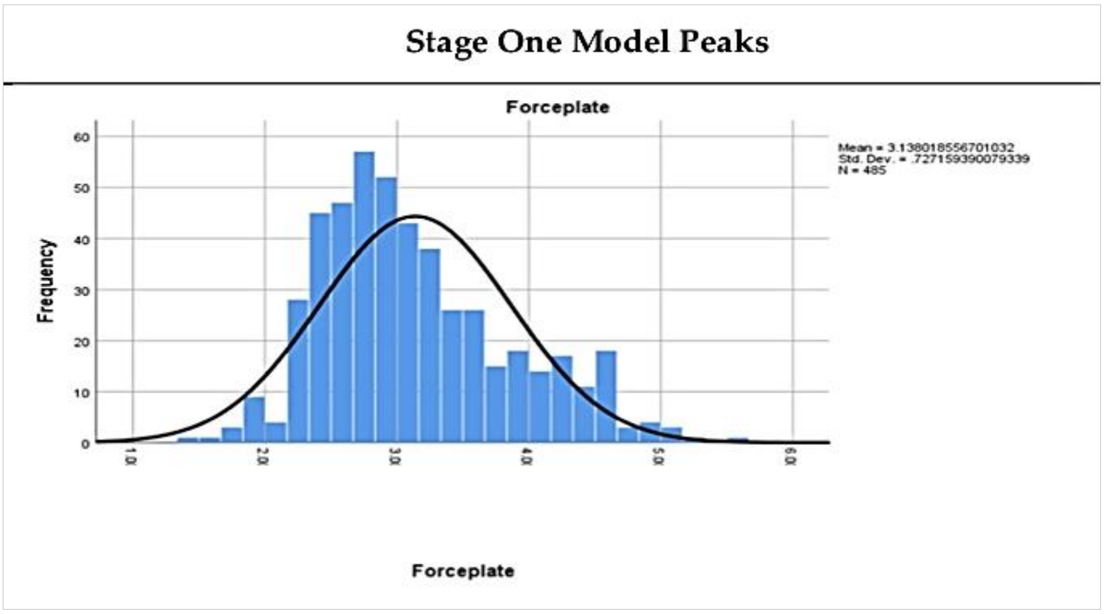
Appendix G
Study 2A: Description of Tasks

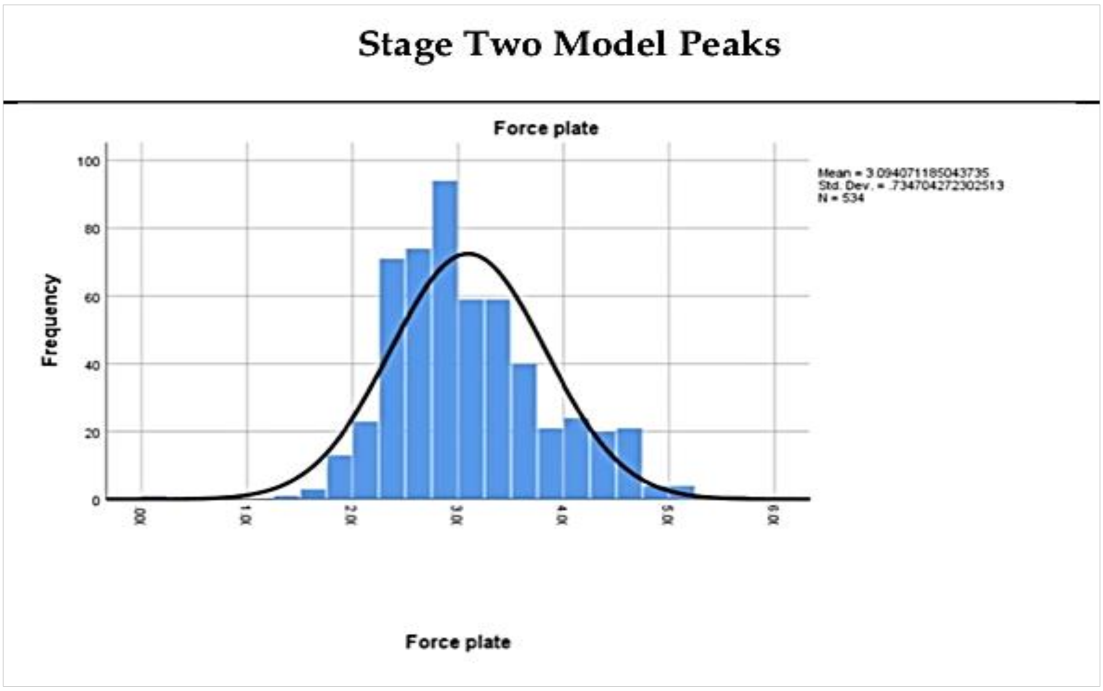
Name	Description	Image demonstrating movement
Bilateral Landings		
Sauté in first position	The dancer commences in first position of the feet (lower limbs externally rotated and heels placed together) and performs 8 bilateral vertical jumps landing bilaterally.	
Changement in 5th position	The dancer commences in fifth position of the feet (lower limbs externally rotated and feet crossed) and performs 8 vertical jumps changing the front foot upon landing.	
Entrechat Quatre	The dancer commences in fifth position of the feet (lower limbs externally rotated and feet crossed) and performs 4 vertical jumps beating the legs in air before landing bilaterally with the same foot in front. This was performed with the right leg and left leg starting in front.	

Name	Description	Image demonstrating movement
Unilateral Landings		
Assemblé	The dancer commences in 5th position and swishes one leg out to the side as they take off, they gather the legs in the air together and land before immediately taking off for the next jump.	
Jeté ordinaire	The dancer commences in 5th position and swishes one leg out to the side as they take off, they then land on the limb that they swished to the side.	
Temps levé	A single leg vertical jump and land performed 5 times in succession.	

Appendix H

Study 2A: Frequency Histograms Representing Data Distribution





Appendix I
Study 2B: Segment Orientations

Plug in Gait Model coordinates for thigh and thorax

Segment	Origin	Axis 1	Axis 2	Axis 3
Thigh	Mid point of femoral epicondyles	Z: Origin to the centre of the femoral head	Y: Between epicondyles (knee flexion axis)	Cross product between axis 1 and 2
Thorax	Mid point anterior surface of clavicular heads	Z:Mid clavicle (C7) to mid sternum (T10)	X: In an anterior direction from the origin	

Appendix J
Study 2B: Model Architecture Description

Initial experimentation and final model architecture details

Initial experimentation was performed utilizing neural networks, with a number of different neural network architectures explored with various parameters, such as individual single input and output models for the three leg lifts utilising the Keras Sequential API, and combined models with multiple outputs utilising the Keras Functional API. A single input, multiple output model designed with the Keras Functional API incorporating a recurrent neural network long short term memory layer delivered the best results.

The final model architecture consisted of a shared input model with three outputs returned; a prediction for leg (left or right) and estimations for thigh elevation angle and lumbar spine sagittal plane angle at each timestep, where there were 100 data points per second (100 Hz). A single input layer was connected to a masked layer, which then passed inputs to 2 separate hidden layers. As the sequence lengths (i.e. number of data points of each individual movement) were variable, the masking layer was used. This is where the sequences were padded to the maximum sequence length of 1068 data points, with data points with the masking input value ignored by the masking layer. A single hidden dense layer with 57 units extracted the features from the sequences, followed by a fully connected dense output layer with sigmoid activation that returned a prediction for the side of the leg (ranging from 0 (right) to 1 (left)). A single long short-term memory (LSTM) hidden layer with 128 un extracted the features from the sequences, followed by 2 separate fully connected time distributed output layers with linear activation returning estimations for thigh elevation angle and lumbar spine sagittal angle.

The number of input units was 15, and consisted of the 2 types of sensors (accelerometer and gyroscope) three planes (x, y and z), for 2 thigh sensors and categorical inputs for the direction of leg lift (back, front or side, researcher supplied). The optimization algorithm applied to the whole model was the adaptive momentum (Adam), a popular algorithm in the field of deep learning due to its fast and accurate performance. The final model parameters were selected after an optimization process assessing the model metrics (i.e. accuracy of the model: accuracy, RMSE, MAE) and loss function (RMSE, MAE, binary cross-entropy) for side of leg, and thigh elevation angle and lumbar spine sagittal plan angle, respectively. For each timestep within each trial, leg prediction values were rounded to 0 (right leg) or 1 (left leg), with the value of the mode determining the final prediction of the leg. The predicted values for thigh elevation angle and lumbar spine sagittal plane angle at each timestep for each movement were smoothed using a Savitzky-Golay filter with a window size of 51 and polynomial order of three. The Savitzky-Golay filter is a particular type of low-pass filter that is well adapted for data smoothing. The window size and polynomial order were selected after an optimization. The peak thigh elevation and lumbar spine sagittal plane angles were determined by extracting the maximum angle of the smoothed curve.

Appendix K
Study 3: Ethics Approval

Curtin University

Office of Research and Development

GPO Box U1987
Perth Western Australia 6845

Telephone +61 8 9266 7863
Facsimile +61 8 9266 3793
Web research.curtin.edu.au

13-Oct-2017

Name: Amity Campbell
Department/School: School of Physiotherapy and Exercise Science
Email: A.Campbell@curtin.edu.au

Dear Amity Campbell

RE: Ethics Office approval
Approval number: HRE2017-0726

Thank you for submitting your application to the Human Research Ethics Office for the project **An investigation of quality of movement and pain related disability in pre-professional dancers**.

Your application was reviewed through the Curtin University Low risk review process.

The review outcome is: **Approved**.

Your proposal meets the requirements described in the National Health and Medical Research Council's (NHMRC) *National Statement on Ethical Conduct in Human Research (2007)*.

Approval is granted for a period of one year from **13-Oct-2017** to **12-Oct-2018**. Continuation of approval will be granted on an annual basis following submission of an annual report.

Personnel authorised to work on this project:

Name	Role
Hendry, Danica	Student
Campbell, Amity	CI
O'Sullivan, Peter	Supervisor
Straker, Leon	Supervisor
Hopper, Luke	Co-Inv

Approved documents:

Document

Standard conditions of approval

1. Research must be conducted according to the approved proposal
2. Report in a timely manner anything that might warrant review of ethical approval of the project including:
   - proposed changes to the approved proposal or conduct of the study
   - unanticipated problems that might affect continued ethical acceptability of the project
   - major deviations from the approved proposal and/or regulatory guidelines
   - serious adverse events
3. Amendments to the proposal must be approved by the Human Research Ethics Office before they are implemented (except where an amendment is undertaken to eliminate an immediate risk to participants)
4. An annual progress report must be submitted to the Human Research Ethics Office on or before the anniversary of approval and a completion report submitted on completion of the project
5. Personnel working on this project must be adequately qualified by education, training and experience for their role, or supervised
6. Personnel must disclose any actual or potential conflicts of interest, including any financial or other interest or affiliation, that bears on this project
7. Changes to personnel working on this project must be reported to the Human Research Ethics Office
8. Data and primary materials must be retained and stored in accordance with the Western Australian University Sector Disposal Authority (WAUSDA) and the Curtin University Research Data and Primary Materials policy
9. Where practicable, results of the research should be made available to the research participants in a timely and clear manner
10. Unless prohibited by contractual obligations, results of the research should be disseminated in a manner that will allow public scrutiny; the Human Research Ethics Office must be informed of any constraints on publication
11. Approval is dependent upon ongoing compliance of the research with the Australian Code for the Responsible Conduct of Research, the National Statement on Ethical Conduct in Human Research, applicable legal requirements, and with Curtin University policies, procedures and governance requirements
12. The Human Research Ethics Office may conduct audits on a portion of approved projects.

Special Conditions of Approval

None.

This letter constitutes low risk/negligible risk approval only. This project may not proceed until you have met all of the Curtin University research governance requirements.

Should you have any queries regarding consideration of your project, please contact the Ethics Support Officer for your faculty or the Ethics Office at hrec@curtin.edu.au or on 9266 2784.

Yours sincerely

Signature Redacted

Amy Bowater
Acting Manager, Research Integrity

Appendix L

Study 3: Recruitment Information Session Outline

Information Session Outline

- Explain where the researchers are from and that this is part of a PhD student project- *have participant information sheets being passed around*
- Brief background on what the research study is about
    - Pain related disability is common in dancers and can be influenced by a number of factors including psychological (thoughts and feelings and psychological distress), lifestyle (sleep) and physical factors (training volume). Currently the mechanism as to how pain related disability links to these is unclear, however it may be due to changes in quality of movement secondary to these factors.
- We are looking for pre-professional and professional female dancers aged between 18 and 30 to take part in this project to help us explore this relationship
- Participation in this study is optional. If you do not want to participate in the study it will not affect your further training or your position in the course
- What testing will involve:
    - Sign an informed consent sheet which will include and optional consent for the data we collect to be used in future studies
    - Have some basic baseline information collected which will include a questionnaire about any pre-existing medical conditions and pain experienced and measurement of height and weight
    - Throughout semester 1 you will be asked to take part in 4 one day data collections where you will be required to do the following:
        - You will wear a wearable sensor set throughout the day which will be applied in the morning by one of the researchers here at WAAPA- this will include 3 sensors which will be small and not encroach on your movement or participation in dance classes. We anticipate this will take 2 minutes to put on. This will provide us with information about specific movement patterns- both in terms of how frequently you perform them and different characteristics of your movement quality such as how high you jump and how heavily you land
        - You will fill in a short questionnaire which will take approximately 5 minutes and will have questions surrounding pain and your thoughts about pain, mood, stress and sleep.
        - At the end of each technique class (ballet and contemporary) and at the end of the day you will be asked to give a score out of 10 as to how much you feel you exerted yourself that day
    - Between each testing session if you experience pain that impacts your dancing or other parts of your life, you will be asked to report this to the researchers and will be asked to fill out a short questionnaire about this pain
- By taking part in this study you will be assisting in developing further understanding about the factors that contribute to pain in dancers. Furthermore, this is an opportunity that you can learn more about yourself as a dancer and what may be influencing your own pain. After the semester, if you would like, you will be provided with a comprehensive report of your own data.

Appendix M
Study 3: Participant Information and Consent Form

Curtin University

PARTICIPANT CONSENT FORM

HREC Project Number:	HRE-2017-0726
Project Title:	*An investigation of pain related disability and quality of movement in pre-professional dancers*
Principal Investigator:	*Dr Amity Campbell*
Co-investigators	*Danica Hendry* *Prof Leon Straker* *Prof Peter O'Sullivan* *Dr Luke Hopper*
Version Number:	
Version Date:	*17/05/2017*

Invitation statement
This is an invitation to participate in a research study which is part of a student PhD project. Please take your time to read and understand the following information about why the study is being conducted and what it will involve. Do not hesitate to ask us if you need any clarification or if you would like more details. This information sheet will help you decide whether or not to take part in the study.

What is the research study about?
Pre-professional ballet dancers commonly experience pain which can affect their participation in dance (modified participation or having to miss classes, rehearsals and performances) and other components of their life. We term this as pain related disability, and it can have a substantial impact on a dancer's quality of life and dance career. A number of factors contribute towards pain related disability, and we are specifically interested in the psychological factors including dancers' thoughts and beliefs around pain and psychological distress, lifestyle factors such as sleep and physical factors such as training volume. A dancer's quality of movement may also impact pain related disability. While previous studies have considered the impact of each of these factors on pain related disability independently, few studies of dancers have analysed them together, nor examined the mechanisms linking these factors and disability.

This study will aim to determine if pain related disability can be predicted by psychological (cognitive and psychological distress), lifestyle (sleep), physical factors (physical workloads) and quality of movement. We will also endeavour to explore if there is a relationship between psychological, lifestyle and physical factors with dancer's quality of movement.

Why am I being asked to take part?
We are recruiting pre-professional female dancers currently enrolled in a tertiary level dance course at The Western Australian Academy of Performing Arts (WAAPA), aged between 18 and 30 to take part in this project.

Do I have to take part in this research study?
Participation in this study is optional. Once you have read this information sheet we are happy to answer any questions you may have. It is then your decision whether or not to volunteer for this project. If you do decide to volunteer, you will then be asked to consent to participate in the study. Following this, you are free to withdraw from the data collection at any time. Your participation in this project will not influence your position in your course of study. There will also be an optional consent for you to sign in relation to future use of the data for related research projects.

What will I have to do if I take part?
If you agree to take part in this study, you will be asked to take part in 4 one day testing sessions throughout a university semester. The timing of these sessions have been decided based around the lead up to and after the first performance season of the year, and will not impact your performances or assessments.

At the beginning of semester, prior to the one week testing blocks we will collect some baseline data (height, weight and a questionnaire detailing medical history and pain). During the one week testing blocks the following will occur:

- You will be asked to wear a wearable sensor set. This will consist of approximately 3-4 small (size of 50c coin) sensors which will be attached to your body (locations to be confirmed following validation studies). These will not impede your movement or effect your participation in classes or rehearsals. You will be asked to wear this for the whole day. These will allow us to measure the amount of times you perform specific movements such as jumps and turns and information about these movements such as how high you are jumping and information about how you are balancing when you turn. The sensors will be fitted in the morning prior to your first scheduled class for the day and taken off at the end of your scheduled training that day (time burden: <2 minutes per person).

- Prior to your scheduled training, you will be asked to fill out a battery of short questionnaires surrounding your pain, thoughts around pain, stress, mood, sleep and fatigue. This will be done online via a website that you can access via your phone, tablet or computer. We will provide paper copies of questionnaires if you would prefer this. We anticipate that this will take 5 minutes per day. You will get a reminder via SMS to fill this out and will also be reminded verbally when we apply your wearable sensor set each day.
- Following your first dance class of the day you will perform 5 maximal hops on each leg. As every dance class has large amounts of variability this will provide a single task that all dancers will perform each day.
- Following each technique class (ballet and contemporary) and at the end of the day, after scheduled training you will be required to answer one more question about how hard you felt you worked that day.

A researcher will be present at WAAPA throughout testing to answer any questions and for any troubleshooting/ problems with wearable sensors and online questionnaires.

In the weeks between testing days, should you experience any pain that affects your participation in dance classes or impacts you in the rest of your life, or if they were to experience an acute traumatic incident they will be asked to contact the researchers. You will be required to complete the questionnaires about pain and the impact of this pain. In the case of the acute traumatic incident and describe what occurred (for example a sprained ankle or a fracture), where you experienced pain and if you are seeing a health professional for this.

What are the possible risks, inconveniences and any discomfort?
You may experience some mild discomfort at the end of the day when we take off the wearable sensors as some of them will be taped on. We understand that there is a time commitment that has been asked of you with applying the sensors and the online questionnaires, however we anticipate that this won't be more than 10 minutes per day in total. Participating in this study will have no impact on your participation in your course.

What are the possible benefits of taking part?
If you take part in this study, you will be exposed to technology that is used within the professional sporting arena to measure training volumes and characteristics of movement as and may become common in dance companies in the future. You will also be utilising questionnaires that are commonly used in sporting teams to monitor athletes' wellness. This is a growing area of interest in dance medicine. The outcomes of this study will allow for improved understanding of the factors that contribute towards pain related disability and quality of movement in dancers. You will also gain insight into the data collection process for a dance related science project which will assist you in broadening your understanding of the different fields and career pathways within dance. Finally, following participation in this study, if you would like a comprehensive report surrounding your own patterns of pain, quality of movement and the factors contributing towards this will be made available on request.

Will my data be kept confidential
At the beginning of semester you will be given a participant number. The researchers will have a record of your number but data recorded will use this number, not your name. Your data will thus be de-identified from the time of data collection. Your results will not be identifiable as belonging to you by anyone other than the research team. All electronic data will be stored on a password protected computer drive which only the research team will be able to access. All physical data (such as questionnaires) will be kept in a locked cabinet located within a secure office in the School of Physiotherapy and Exercise Science at Curtin University. All data will be kept for 7 years.

What will happen to the results of the research study?
The results of this study will be published in one or more scientific journals and presented at scientific conferences.

What happens next and who can I contact about the research?
If you would like to know more at any stage, please feel free to contact Danica Hendry, who will be happy to discuss this information with you further and answer any questions you may have.
Danica's contact details are:
Tel: 0421556854 or Email: danica.hendry@postgrad.curtin.edu.au.

If you decide to take part in this research, we will ask you to sign the consent form. By signing it is telling us that you understand what you have read and what has been discussed Please take your time and ask any questions you have before you decide what to do. You will be given a copy of this information and the consent form to keep.

Thank you for considering participating in this study.

Curtin University Human Research Ethics Committee (HREC) has approved this study (HRE 2017 0726). Should you wish to discuss the study with someone not directly involved, in particular, any matters concerning the conduct of the study or your rights as a participant, or you wish to make a confidential complaint, you may contact the Ethics Officer on (08) 9266 9223 or the Manager, Research Integrity on (08) 9266 7093 or email hrec@curtin.edu.au.

- I have read the participant information sheet and I understand its contents.
- I believe I understand the purpose, extent and possible risks of my involvement in this project.
- I voluntarily consent to take part in this research project and I can withdraw at any time of the study without complications
- I have had an opportunity to ask questions and I am satisfied with the answers I have received.
- I understand that my data will be re-identified while confidentiality is maintained at all times to ensure my privacy.
- I understand that this project has been approved by Curtin University Human Research Ethics Committee and will be carried out in line with the National Statement on Ethical Conduct in Human Research (2007).
- I understand I will receive a copy of this Information Sheet and Consent Form.

Participant's Name	
Participant's Signature	
Date	

<u>Optional Consent</u>

- I do consent to the storage and use of my information in future ethically-approved research projects related to this study.

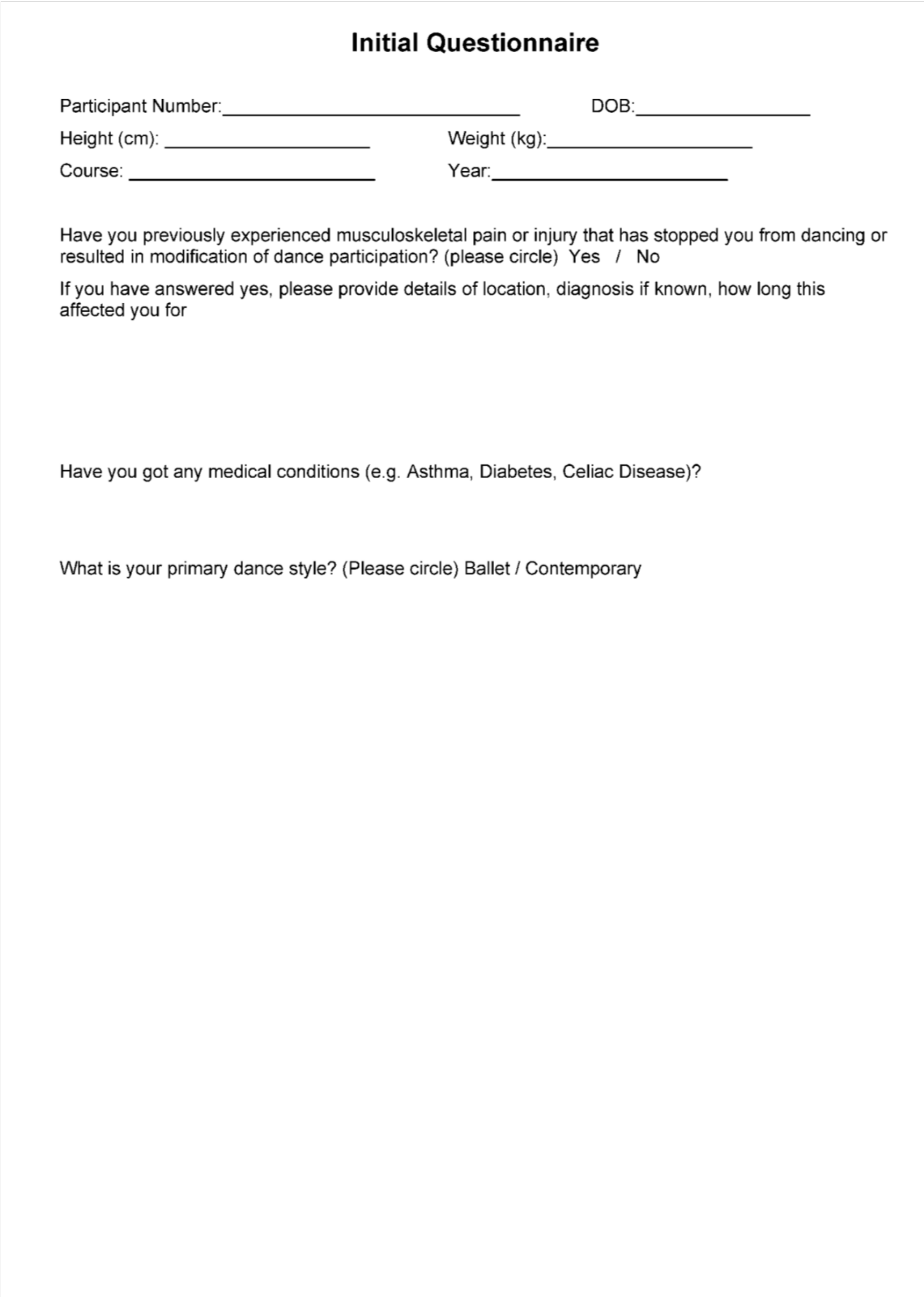
Participants Name	
Participants Signature	
Date	

<u>Declaration by researcher:</u>

I have supplied an Information Statement and Consent Form to the participant who has signed above, and believe that they understand the purpose, extent and possible risks of their involvement in this project.

Researcher's Name	
Researcher's Signature	
Date	

Appendix N
Study 3: Questionnaires



Initial Questionnaire

Participant Number:______________________________ DOB:_________________

Height (cm): ____________________ Weight (kg):____________________

Course: ________________________ Year:_______________________

Have you previously experienced musculoskeletal pain or injury that has stopped you from dancing or resulted in modification of dance participation? (please circle) Yes / No

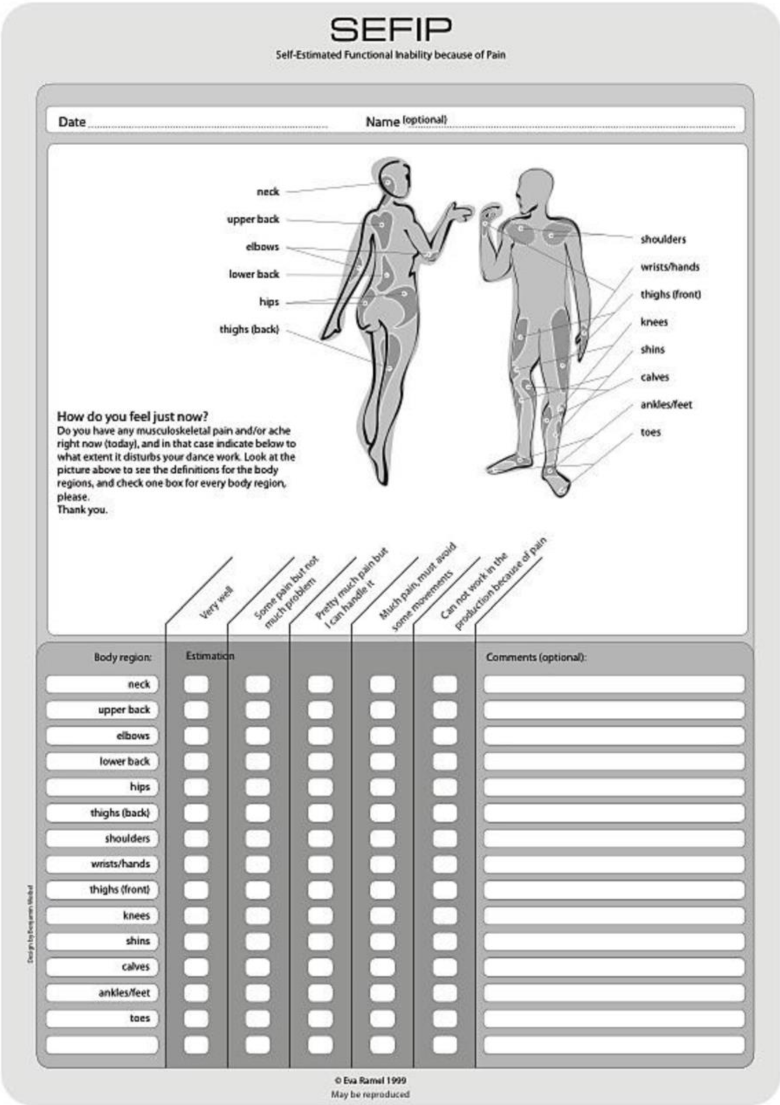
If you have answered yes, please provide details of location, diagnosis if known, how long this affected you for

Have you got any medical conditions (e.g. Asthma, Diabetes, Celiac Disease)?

What is your primary dance style? (Please circle) Ballet / Contemporary

Questionnaires answered at each time point

Please fill in the SEFIP based on any pain you are experiencing today. In the comments box, please place a pain score (0-10, where by 0 represents no pain and 10 is the worst pain you can imagine).



SEFIP

Self-Estimated Functional Inability because of Pain

Date .... Name (optional) ....

neck, upper back, elbows, lower back, hips, thighs (back), shoulders, wrists/hands, thighs (front), knees, shins, calves, ankles/feet, toes

How do you feel just now?
Do you have any musculoskeletal pain and/or ache right now (today), and in that case indicate below to what extent it disturbs your dance work. Look at the picture above to see the definitions for the body regions, and check one box for every body region, please.
Thank you.

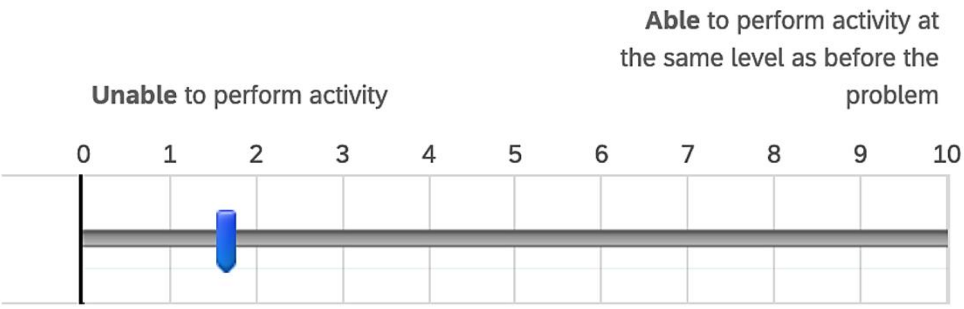
Body region:	Estimation: Very well	Some pain but not much problem	Pretty much pain but I can handle it	Much pain, must avoid some movements	Can not work in the production because of pain	Comments (optional):
neck						
upper back						
elbows						
lower back						
hips						
thighs (back)						
shoulders						
wrists/hands						
thighs (front)						
knees						
shins						
calves						
ankles/feet						
toes						

Design by Benjamin Wedel

Of the pains you have indicated above, which pain do you feel is bothering you the most today? Please attempt to select one option, however if you feel that there are multiple areas that are most bothersome, please select all that apply to you, and this will indicate that your pain is widespread.

Patient Specific Functional Scale

Today, are there any activities that you are unable to do or having difficulty with because of your _______________ pain? Please select up to 3 activities, if you have selected less than 3 please leave the remaining sections blank.


Able to perform activity at the same level as before the problem
Unable to perform activity
0
1
2
3
4
5
6
7
8
9
10

Appendix O

An exploration of pre-professional dancers' beliefs of the low back and dance-specific low back movements

Article

An Exploration of Pre-Professional Dancers' Beliefs of the Low Back and Dance-Specific Low Back Movements

Danica Hendry, MSc,[1] Leon Straker, PhD,[1] Amity Campbell, PhD,[1] Luke Hopper, PhD,[2] Rhianna Tunks, BSc,[1] and Peter O'Sullivan, PhD[1]

OBJECTIVE: Low back pain (LBP) is common in dancers. A biopsychosocial model should be considered in the aetiology of LBP, including a dancer's general beliefs of the low back and movements of the spine. This study aimed to determine pre-professional dancers' beliefs about their lower back in general and dance-specific movements of the spine and to explore whether these beliefs were influenced by a history of disabling LBP. **METHODS:** 52 pre-professional female dancers (mean age 18.3 [1.4] yrs) were recruited and reported whether they had a history of disabling LBP and completed the Back Pain Attitudes Questionnaire (Back-PAQ) and a dance movement beliefs questionnaire. A linear mixed model was applied to determine the effect of a history of disabling LBP on dancers' beliefs (p<0.05). **RESULTS:** 20 dancers reported a history of disabling LBP. Regardless of this LBP history, dancers held generally negative beliefs as measured by the Back-PAQ (p=0.130). A history of disabling LBP did not influence dancers' perceived movement safety of all tasks (p=0.867), and dancers held negative beliefs towards extension activities. These beliefs were linked to the conceptions of perceived risk of damage and the need to protect the lower back. **CONCLUSIONS:** Dancers hold negative general beliefs around the low back and low back movements, regardless of a history of disabling LBP. Dancers perceive extension activities as more dangerous than flexion activities. These beliefs may reflect a combination of pain experience and beliefs specific to dance. *Med Probl Perform Art* 2019;34(3):147-153.

From the [1]School of Physiotherapy and Exercise Science, Curtin University, Perth, and [2]Western Australian Academy of Performing Arts, Edith Cowan University, Perth, Western Australia.

Supported by a Research Training Program Scholarship and Curtin University Postgraduate Scholarship (DH). The authors declare no conflicts of interest related to this study.

Presented at the Sports Medicine Australia 2018 Conference, Oct. 2018, and at the Australian Society for Performing Artist's Healthcare 2018 Conference, Dec. 2018.

Address for correspondence: Ms. Danica Hendry, School of Physiotherapy and Exercise Science, Curtin University, GPO Box U1987, Perth, WA 6845, Australia. Tel 0421 556 854. danica.hendry@curtin.edu.au.

https://doi.org/10.21091/mppa.2019.3025

Low back pain (LBP) is commonly experienced by dancers and can be highly disabling,[1,2] resulting in substantial time loss from dance classes, rehearsals, and performances.[2] A recent investigation exploring the prevalence of LBP in Australian dancers demonstrated a lifetime prevalence of 74%.[3,4] Over half of the dancers in this study considered their previous experience of LBP to be disabling, whereby dance activity had been missed or modified due to the LBP.[4]

LBP in female dancers is commonly cited as being the outcome of repetitive overload.[3,5] Within training and performance, classical and contemporary dancers perform repeated, cyclical, multiplanar movements of the spine and limbs, frequently towards the end of their physiological range of motion.[3,6] Specifically, dance is characterised by repeated movements in extended and hyperextended lumbar spine postures, and dancers commonly present clinically with back pain that is aggravated by extension-based movements with and without loading.[7] It is thought that these repetitive movements to the lumbar spine for some may lead to the development of lumbar stress fractures and spondylolysis.[8] However radiographic findings are not always well correlated with disabling LBP (DLBP); for example, 33% of adolescent asymptomatic cricket fast bowlers and 27% of asymptomatic adolescent tennis players demonstrate radiographic evidence of lumbar spine pars defects.[9,10] These findings suggest that the presence of pathology on radiography and mechanical loading are not independently causative of LBP.[11,12] A contemporary view of LBP supports that LBP is a complex condition with different biopsychosocial contributing factors.[13,14]

Within the biopsychosocial spectrum, it is important to consider psychological and social factors, inclusive of an individual's belief system regarding the lower back, LBP, and functional movements involving the lumbar spine.[13] Negative back pain beliefs are prevalent in both those with and without LBP across age groups, where the pervasive view is that the spine is a vulnerable structure that is easily injured, hard to heal, and requires protection.[15] Negative beliefs are associated with greater levels of disability, sick leave and health care seeking, thereby influencing an individual's trajectory.[16–19]

While most studies historically have examined LBP beliefs relating to activity, rest, and work,[16,20,21] more recent studies have explored back pain beliefs specific to spinal postures and activities.[18,19,22] For example, people in the general population with[22] and without LBP[18] believe that lifting with a round back (flexed lumbar spine) is more dangerous than lifting with a straight back (extended lumbar spine). Similarly, 75% of physiotherapists and 91% of manual handling specialists (n=400) indicated that they believed a straight back lifting posture was safer than a round back posture.[19] Furthermore, the participants who selected a straight back posture as safe demonstrated more negative beliefs surrounding the lower back than those who selected a round back posture as safe.[19] These findings highlight that people with and without back pain have back pain beliefs regarding specific spine postures and activities, in spite of limited evidence supporting this view.[23] It has been proposed that these beliefs may directly influence a person's behavioural response to the presence of back pain (i.e., how a person postures or protects their spine).[22]

While a number of studies have demonstrated dancers' perceptions and beliefs surrounding pain and injury in general,[24–27] to date only one study has specifically explored back pain beliefs in dancers (n=40).[28] Roussel et al. reported there was no difference between pain beliefs regarding fear of movement in dancers with a history of LBP compared to those without (Tampa Scale of Kinesiophobia, mean score = 34.2 and 36.2, respectively, p=0.293).[28] To date no studies have explored the beliefs that dancers hold specifically in relation to their lower back posture, during commonly practised, functional movement patterns, and its relationship to LBP. This knowledge would provide greater insight into the back pain beliefs of dancers with regards to movements commonly reported to provoke LBP.[7,8]

Thus, the primary aim of this study was to investigate dancers' beliefs about LBP in general, as well as dance-specific movements, while accounting for the potential influence previous experience of DLBP has on these beliefs. The secondary aim was to explore why dancers hold these beliefs.

METHODS

Participants

One hundred pre-professional female dancers enrolled in a full-time dance training program at the Western Australian Academy of Performing Arts training facility were invited to participate in this study via information sheets and participant recruitment sessions at the university. Female dancers were eligible to participate if they were over the age of 16 and were currently enrolled in one of the full-time dance programs at the university, where dancers trained primarily in classical and contemporary dance. Fifty-two dancers expressed interested in participating in the study and consented to participate (mean age 18.5 [1.1 SD] yrs). Ethical approval was provided by the Curtin University Human Research Ethics Committee (HRE2017-0185). Written informed consent from the dancers was obtained.

Data Collection

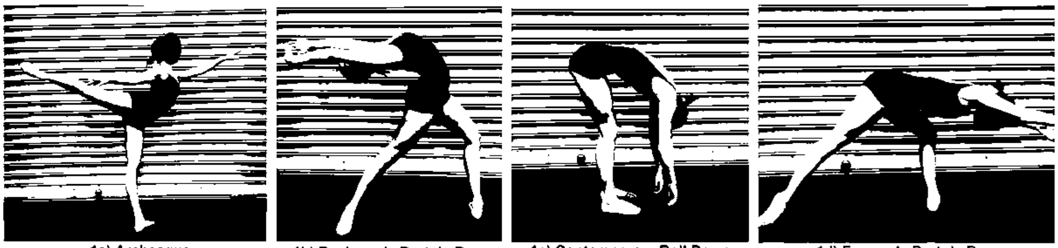
Dancers underwent a brief (2–5 minutes) interview with one of the researchers, detailing any history of DLBP. Two of the researchers conducted the interview, one was a qualified sports physiotherapist and the other a final-year physiotherapy student. Both had a background in ballet and contemporary dance. Dancers were asked if they had previously experienced pain that stopped them from dancing or resulting in modification of dance participation for a day or more. This was defined as DLBP.[4] Dancers were then asked to independently complete an electronic survey using Qualtrics (Qualtrics, Seattle, WA, USA). The electronic survey had four sections: demographic details, the Back Pain Attitudes Questionnaire (Back-PAQ), the Dance Movement Beliefs Questionnaire, and a single open question asking about dancers' rationale for their beliefs with a written response.

Demographic Data—Demographic data collected included age, years of dance experience, the specific course and year level the dancer was enrolled in, and whether they identified as a ballet or contemporary dancer.

Back-PAQ—The Back-PAQ questionnaire compromises 34 Likert-style items, each with 5 possible responses and with 6 subscales.[29] The items pertain to beliefs surrounding the back (2 subscales), the individual's beliefs about their own back (2 subscales), management of back pain and attitudes about recovering from back pain (2 subscales). The questionnaire has been shown to be reliable and valid with adequate internal consistency.[29] Scores from these items were summed to provide an indication of back pain beliefs. A range of scores from 34 to 170 is possible, whereby higher scores are indicative of more negative beliefs about the lower back.[29]

Dance Movement Beliefs Questionnaire—A questionnaire was developed to determine dancers' perceived level of safety of different dance-specific movements. Dancers were presented with four images of a ballet dancer performing specific movements, each incorporating multiplanar movements of the lumbar spine (Fig. 1). The movements were selected based on the report of LBP being caused by repeated end-of-range movement[6] and following consultation with professional colleagues including dancers, dance teachers, and clinicians who work with dancers. The positions were selected on the basis that these are frequently performed by female dancers within both ballet and contemporary dance and within the scope of movements performed away from the ballet barre in class and in performance and are reported to be associated with LBP.

An 18-year-old female dancer, not included in the study but of similar ability to the dancers surveyed, was photographed performing the movements to generate the images. Two of the images depicted lumbar spine extension; a *backwards port de bras*, and an *arabesque* (Fig. 1a, 1b), and the other two demonstrated the dancer in flexed lumbar spine postures: a *forwards port de bras* and a *contem-*



1a) Arabesque 1b) Backwards Port de Bras 1c) Contemporary Roll Down 1d) Forwards Port de Bras

FIGURE 1. Movement Safety Questionnaire images and movements.

porary roll down (Fig. 1c, 1d). Participants were instructed to use a 10-point thermometer scale to demonstrate how safe or dangerous they perceived the movement to be, with the written instructions: "*For each of the movements shown in the images please indicate how safe you believe the movement is for your lower back.*" (Scores ranged from 0 = completely safe to 10 extremely dangerous.)

Single Written Open Qualitative Question Dancers were asked to select whether they believed flexion or extension activities were more dangerous for their back. They were then presented with a single written open question in the electronic survey with reference to their response to the previous question "*Why do you believe flexion/extension activities are more dangerous?*" and were provided with a space to record their written response. Dancers recorded their response independently without prompting from the researchers.

Statistical Analysis

For power calculation, a post-hoc power analysis was performed using G*Power ver. 3.1, demonstrating an observed power of 0.17. The sample characteristics were summarised descriptively using means and standard deviations (SD). A linear mixed model was applied to determine if there were differences between the dancers with a history of DLBP and those without DLBP (non-DLBP) in the responses to the Back-PAQ and Dance Movement Safety Questionnaire. As a secondary analysis, a linear mixed model was applied to determine which movement dancers across both groups determined as safest. An alpha level was set at 0.05. Statistical analyses were completed using SPSS (ver. 23; SPSS-IBM, Armonk, NY, USA). All written text responses for the single open question were tabulated. Key phrases were subsequently highlighted by the investigators and identified as themes that emerged from the single open written question.

RESULTS

Of the 52 dancers surveyed, 20 reported a history of DLBP. All dancers were Australian. Demographics of the dancers participating in the study are presented in Table 1. There were no significant differences in the demographics of dancers with and without a history of DLBP.

Back Pain Attitudes Questionnaire (Back-PAQ)

Participants' total scores for the Back-PAQ ranged from 90 to 129 within the possible range of 34 to 170. There was no significant difference in Back-PAQ scores between dancers with a history of DLBP and those without, whereby all dancers demonstrated negative beliefs: DLBP mean 111.2 (9.8), SE 2.2; non-DLBP mean 113.0 (6.5), SE 1.1 (p 0.130).

Dancers' Perceived Movement Safety Rating

Linear regression showed that there was no difference (p=0.867) in the safety rating between dancers with and without a history of DLBP (Fig. 2). However, there was a difference (p<0.001) in the safety ratings across movements, with pairwise comparisons showing dancers perceived the contemporary roll down as the safest movement when compared with all other movements and the backwards *port de bras* was perceived as the most dangerous (Table 2).

Dancers Perceptions of Flexion and Extension Tasks

When asked whether they perceived flexion or extension tasks as more dangerous, 47 of the 52 dancers selected extension tasks and 5 selected flexion tasks. Dancers' reasons for selecting extension movements reflected two common themes: experience of pain with extension activities and cultural beliefs within the dance industry, and an overlap between the two whereby dancers related the cultural beliefs of the dance industry to the potential experience of pain (Fig. 3). Six of the dancers linked their beliefs to the experience of pain when moving into extended postures, and 6 directly related extension movements with a risk of potential pain and "injury."

TABLE 1. Participant Demographics

	All Dancers	DLBP	Non-DLBP
Age (yrs)	18.4 (1.1)	18.3 (1.3)	18.5 (1.1)
Height (cm)	168.4 (5.4)	168.8 (5.9)	168.2 (5.2)
Weight (kg)	59.5 (5.8)	59.6 (6.7)	59.5 (5.4)
Dance experience (yrs)	13.5 (3.1)	13.1 (3.2)	13.7 (3.1)
Dance style (ballet/contemp.)	24/28	9/11	15/17

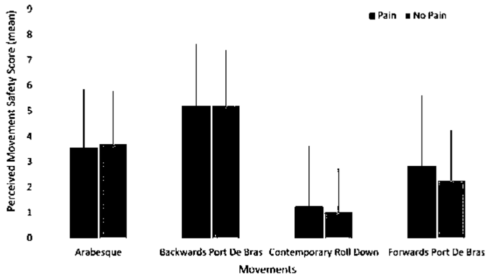


FIGURE 2. Dancers' perceived movement safety score for each movement task (*dark bars*, pain; *light bars*, no pain).

Half of the dancers who rated extension activities as more dangerous associated these activities with an increase in "load," "strain," "impact," "pressure," "compression," and "stress" on the lumbar spine. Nine of these dancers related the words "crush" and "crunch" to extension movements of the lumbar spine. Dancers also related the increase in loading on the lower back to incorrect technique or reduced technical capacity. One dancer described, "*If extensions of the spine are not performed correctly, crunching in the lower back can occur which may lead to injury.*" Another dancer described their perception of extension movements as "*crushing of the vertebrae, if the movement is performed incorrectly, especially if sinking into the lower back.*"

All of the dancers who perceived flexion tasks as more dangerous related it to either a previous history of pain (n=2) or a risk of future pain experience and potential damage (n=4).

TABLE 2. Dancers' Movement Safety Perception Scores Reflecting Pairwise Comparisons

	Mean Diff.	*p*-Value	95% CI LB	95% CI UB
Arabesque (extension)				
Backwards port de bras	1.6	<0.001	−2.448	−0.702
Contemporary roll down	2.5	<0.001	1.621	3.366
Forwards port de bras	2.6	0.018	0.180	1.926
Backwards *port de bras* (extension)				
Arabesque	1.6	<0.001	0.702	2.448
Contemporary roll down	4.1	<0.001	3.196	4.941
Forwards port de bras	2.6	<0.001	1.755	3.501
Contemporary roll down (flexion)				
Arabesque	2.5	<0.001	−3.366	−1.621
Backwards port de bras	4.1	<0.001	−4.941	−3.196
Forwards port de bras	1.4	0.001	−2.313	−0.568
Backwards *port de bras* (flexion)				
Arabesque	1.1	0.018	−1.926	−0.180
Backwards port de bras	2.6	<0.001	−3.501	−1.755
Contemporary roll down	1.4	0.001	0.568	2.313

CI, confidence interval; LB, lower back; UB, upper back.

DISCUSSION

This is the first study to explore beliefs around LBP specific to dance-related multiplanar spinal movements in dancers with and without a history of DLBP. Thirty-eight percent of the dancers reported a history of DLBP; however, this history did not influence either dancers' general beliefs about the lower back or their perception of movement safety. Instead, the majority of dancers, regardless of a history of DLBP, perceived extension movements as more dangerous than flexion movements.

A history of DLBP was not associated with a dancer's general beliefs of their lower back as measured by the Back-PAQ; instead all dancers held generalised negative beliefs about the back. These findings are consistent with findings from the general population, where regardless of a history of DLBP, a pervasive pessimistic view of the lower back and LBP exists. In fact, dancers with and without a history of DLBP held more negative general beliefs around the lower back than pain-free adults in the general population (n=68, mean Back-PAQ score 105.5),[18] as well as physiotherapists and manual handling specialists with and without a history of DLBP (mean Back-PAQ scores 81.8 and 77.2, respectively).[19] However, the dancers' beliefs about the lower back were not as negative as those of a larger population of adults with current DLBP, a history of DLBP, and pain-free (n=602, mean Back-PAQ score 156),[30] although in that study DLBP was only accounted for at an individual item level and not in the total Back-PAQ score.

The results of the current study are also consistent with previous research exploring pain beliefs in dancers with and with a history of LBP, where dancers demonstrated negative beliefs regarding fear of movement regardless of a history of LBP (Tampa Scale of Kinesiophobia, mean score = 34.2 and 36.2, respectively; p=0.293).[28] Further research is required to investigate dancers' beliefs surrounding the lower back during an episode of DLBP. Our results suggest that dancers, regardless of a history of DLBP, hold a preexisting belief, similar to other populations, that the lower back is vulnerable and easily damaged.

Additionally, the beliefs that the dancers held about posture of their lower back were not influenced by a history of DLBP. This aligns with previous literature where negative beliefs surrounding posture of the lower back are generally common. However, in contrast to prior studies where non-dancing populations have considered flexion postures as dangerous, dancers in this study associated extension postures as dangerous. Within non-dancing populations, there is a common perception that bending and lifting involving a flexed lumbar spine (round back posture) are more dangerous than straight back posture. Goubert et al.[31] assessed the beliefs of adults with and without a history of DLBP[18,19] and demonstrated that both individuals with and without pain perceived the back as vulnerable when engaging in activities involving lumbar spine flexion. These authors concluded that a previous experience of pain did not influence these posture beliefs.[31]

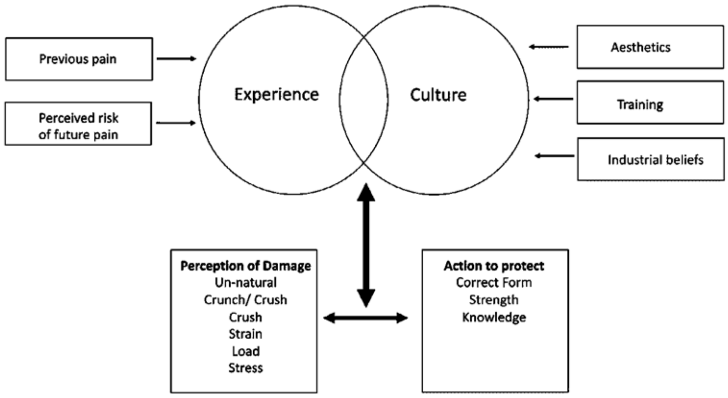


FIGURE 3. Interplay of dancers' qualitative responses.

Similarly, Nolan et al.[19] demonstrated that both physiotherapists and manual handling specialists perceived that lifting with a round or flexed back posture is more dangerous than with a straight back posture. In contrast, 90% of dancers in the current study perceived extension activities as more dangerous, irrespective of a history of DLBP. Specifically, dancers perceived a backward *port de bras* as most dangerous, followed by an *arabesque*, a forward *port de bras,* and contemporary roll down. While speculative, the differences in these beliefs may be due to the experiences and beliefs specific to the dance industry.

A small group of the dancers (*n*=6) who had a history of pain related their posture beliefs to their history of DLBP, describing how they had previously experienced LBP during extension tasks. However, even without pain experience, the majority of dancers related extension movements as dangerous. What underlies these beliefs remains unclear, but it is possible that they are influenced by training and education, the aesthetic attributes of movement in dance,[32] and dance industry beliefs.[24,27]

Dancers commonly reported extension movements as potentially damaging to the lumbar spine. A common belief existed that extension was an unnatural movement for the spine and may result in 'crushing' or 'crunching' the vertebrae, and that extension imposed greater stress, strain, and load on the lumbar spine than flexion activities. They reported that a focus on control of movement, optimal form, alignment, adequate strength, including abdominal muscle strength, as well as understanding of the anatomy of the spine and dance technique can reduce the danger of extending the spine. This aligns with previous literature qualitatively exploring dancers' perceptions and rationales for the development of pain and injury in general.[24,27] McEwen and Young[27] described that dancers frequently reported pain as a sign that they were not executing their technique correctly. Similarly, in a separate qualitative study, most professional dancers described poor technique or mismanagement of their own technique as being a primary contributor to the development of pain and injury.[24] Similar to the responses given by the dancers in the present study, professional dancers reported deficits in muscle strength and muscular imbalances as contributing to back injuries.[24] Considered together, these findings suggest that there is a strong belief within the dance industry that pain and injury are caused by technical divergences and a lack of strength.

It is plausible that dancers develop these beliefs in their training. Research has demonstrated that dancers will commonly approach their teacher as a primary source for advice surrounding injury, pain, and general health.[33] Additionally, teachers instruct within the aesthetic of dance, which is integral to the culture of dance. Pedagogical texts describe these aesthetic requirements, instructing that when moving into extended positions, dancers are encouraged to lengthen through the lumbar spine and move into extension predominantly from the upper back while stabilising through the lower back, activating the lower abdominal musculature to support the lumbar spine.[32] While speculative, it is possible that the cues given to encourage form and strength aligning with the aesthetics and physical requirements of dance influence what is considered as safe or dangerous and that this potentially influences dancers' beliefs about movements of the lumbar spine. Further research is required to investigate dance teachers' perceptions and beliefs surrounding the lower back, as well as the drivers for these beliefs and how they portray these messages to their students.

Drawing upon the model of illness perceptions,[34] it is understood that the way an individual perceives illness, injury, or pain is influenced by history, experience, beliefs, and culture.[23,34] Additionally a person's preexisting beliefs can influence the behaviours they adopt when they experience pain.[23] Dancers' back beliefs can be viewed as a latent network of thoughts surrounding their perceptions of LBP and movements of the spine, reflecting their personal experiences and understanding. These encompass the belief that extending the spine is potentially dangerous and damaging, posing a threat to the dancer. If the dancer were to experience LBP, this latent network of thoughts may become activated and the dancer may feel as though they need to protect their lumbar spine or avoid the movement and or activity and will take action to do so. Previous literature has shown that people who hold more negative LBP beliefs are more likely to avoid physical activity[16] and work[17] as well as tense the muscles of the trunk and move cautiously, resulting in increased spinal loading.[35] Whether this same response occurs in dancers with LBP who hold negative beliefs, especially during dynamic, extension-based tasks, is unknown. Further qualitative and quantitative research is required to further explore these issues. Given the growing evidence for the importance of acknowledging, addressing and challenging back pain beliefs in the prevention[36] and management[14,37] of LBP, it is logical that this practice should extend to dancers with LBP and the dance industry at large.

Strengths and Limitations

This study is the first study to explore both the general and movement-specific beliefs that female dancers hold surrounding the lower back, accounting for a history of DLBP. The study was limited to a small population of Australian, pre-professional, university-level female dancers, with an observed power of 0.17. Although the observed power of the sample is low, the standard error demonstrated in both groups is also low, suggesting that the results are representative of a normal population. Further, it is very unlikely that a difference of 1.8 points in the score on this scale is of any clinical importance. Future research should include male dancers and a greater cross-section of the dance community. Additionally, the movement beliefs explored were limited to multidirectional, end-of-range movements of the lumbar spine without the consideration of added load (such as that seen during lifting tasks). Future research should include a variety of partnering and lifting tasks to allow for exploration of beliefs surrounding loaded movements and postures and should also account for whether dancers have formally learned about the spine and LBP. Such research should also include dancers' attitudes towards and beliefs surrounding the biopsychosocial contributing factors towards the development of LBP.

Conclusions

Dancers with and without a history of DLBP hold generally negative beliefs about the lower back. Dancers perceived lumbar spine extension postures as less safe, which is in contrast to the general population where a pervasive belief that flexed lumbar spine postures are more dangerous exists. Dancers' rationale for their beliefs reflected the potential experience of pain secondary to extension postures and common dance industry beliefs. While further studies are required to explore the basis and impact of these beliefs, the findings have implications for both clinicians and dance teachers in terms of the beliefs that are both reinforced, explored, and challenged with the dancer.

REFERENCES

1. Gamboa JM, Roberts LA, Maring J, Fergus A. Injury patterns in elite preprofessional ballet dancers and the utility of screening programs to identify risk characteristics. *J Orthop Sports Phys Ther.* 2008; 38(3):126–36. https://doi.org/10.2519/jospt.2008.2390.
2. Allen N, Nevill A, Brooks J, et al. Ballet injuries: injury incidence and severity over 1 year. *J Orthop Sports Phys Ther.* 2012; 42(9):781–90. https://doi.org/10.2519/jospt.2012.3893.
3. Swain CTV, Bradshaw EJ, Whyte DG, Ekegren CL. Life history and point prevalence of low back pain in pre-professional and professional dancers. *Phys Ther Sport.* 2017; 25:34–38. https://doi.org/10.1016/j.ptsp.2017.01.005.
4. Swain CTV, Bradshaw EJ, Whyte DG, Ekegren CL. The prevalence and impact of low back pain in pre-professional and professional dancers: a prospective study. *Phys Ther Sport.* 2018; 30:8–13. https://doi.org/10.1016/j.ptsp.2017.10.006.
5. Gildea JE, Hides JA, Hodges PW. Morphology of the abdominal muscles in ballet dancers with and without low back pain: a magnetic resonance imaging study. *J Sci Med Sport.* 2014; 17(5):452–6. https://doi.org/10.1016/j.jsams.2013.09.002.
6. Gildea JE, van den Hoorn W, Hides JA, Hodges PW. Trunk dynamics are impaired in ballet dancers with back pain but improve with imagery. *Med Sci Sports Exerc.* 2015; 47(8):1665–71. https://doi.org/10.1249/MSS.0000000000000594.
7. Khan K, Brown J, Way S, et al. Overuse injuries in classical ballet. *Sports Med.* 1995; 19(5):341–57.
8. Gottschlich LM, Young CC. Spine injuries in dancers. *Curr Sports Med Rep.* 2011; 10(1):40–4. https://doi.org/10.1249/JSR.0b013e318205e08b.
9. Crewe H, Elliott B, Couanis G, et al. The lumbar spine of the young cricket fast bowler: an MRI study. *J Sci Med Sport.* 2012; 15(3):190–4. https://doi.org/10.1016/j.jsams.2011.11.251.
10. Alyas F, Turner M, Connell D. MRI findings in the lumbar spines of asymptomatic, adolescent, elite tennis players. *Br J Sports Med.* 2007; 41:836–841.
11. Roffey DM, Wai EK, Bishop P, et al. Causal assessment of awkward occupational postures and low back pain: results of a systematic review. *Spine J.* 2010; 10(1):89–99. https://doi.org/10.1016/j.spinee.2009.09.003.
12. Wai EK, Roffey DM, Bishop P, et al. Causal assessment of occupational bending or twisting and low back pain: results of a systematic review. *Spine J.* 2010; 10(1):76–88. https://doi.org/10.1016/j.spinee.2009.06.005.
13. O'Sullivan P CJ, O'Keeffe M, O'Sullivan K. Unraveling the complexity of low back pain. *J Orthop Sports Phys Ther.* 2016; 46(11):932–937. https://doi.org/10.2519/jospt.2016.0609.
14. O'Sullivan PB, Caneiro JP, O'Keeffe M, et al. Cognitive functional therapy: an integrated behavioral approach for the targeted management of disabling low back pain. *Phys Ther.* 2018; 98(5):408–423. https://doi.org/10.1093/ptj/pzy022.
15. Darlow B, Dean S, Perry M, et al. Easy to harm, hard to heal: patient views about the back. *Spine (Phila Pa 1976).* 2015; 40(11):842–50. https://doi.org/10.1097/brs.0000000000000901.
16. Smith AJ, O'Sullivan PB, Beales D, Straker L. Back pain beliefs are related to the impact of low back pain in 17-year-olds. *Phys Ther.* 2012; 92(10):1258–67. https://doi.org/10.2522/ptj.20110396.
17. Beales D, Smith A, O'Sullivan P, et al. Back pain beliefs are related to the impact of low back pain in baby boomers in the Busselton Healthy Aging Study. *Phys Ther.* 2015; 95(2):180–9.

https://doi.org/10.2522/ptj.20140064.
18. Caneiro JP, O'Sullivan P, Lipp OV, et al. Evaluation of implicit associations between back posture and safety of bending and lifting in people without pain. *Scand J Pain*. 2018;18(4):719–728. https:// doi.org/10.1515/sjpain-2018-0056.
19. Nolan M OSK, Stephenson J, O'Sullivan P, Lucock M. What do physiotherapists and manual handling advisors consider the safest lifting posture, and do back beliefs influence their choice? *Musculoskelet Sci Pract*. 2018; 33(1):35–40. https://doi.org/10.1016/j.msksp.2017.10.010.
20. Patterson E, Smith R, Everett J, Ptacek J. Psychosocial factors as predictors of ballet Injuries: Interactive effects of life stress and social support. *J Sport Behav*. 1998; 21(1):101.
21. Wand BM, Catley MJ, Rabey MI, et al. Disrupted self-perception in people with chronic low back pain: further evaluation of the Fremantle Back Awareness Questionnaire. *J Pain*. 2016; 17(9):1001–12. https://doi.org/10.1016/j.jpain.2016.06.003.
22. Caneiro JP, O'Sullivan P, Smith A, et al. Implicit evaluations and physiological threat responses in people with persistent low back pain and fear of bending. *Scand J Pain*. 2017; 17:355–366. https://doi.org/10.1016/j.sjpain.2017.09.012.
23. Bunzli S, Smith A, Schutze R, et al. Making sense of low back pain and pain-related fear. *J Orthop Sports Phys Ther*. 2017; 47(9):628–636. https://doi.org/10.2519/jospt.2017.7434.
24. Harrison C, Ruddock-Hudson M. Perceptions of pain, injury, and transition-retirement. the experiences of professional dancers. *J Dance Med Sci*. 2017; 21(2):43–52. https://doi.org/10.12678/1089-313X.21.2.43.
25. Tajet-Foxell B, Rose FD. Pain and pain tolerance in professional ballet dancers. *Br J Sports Med*. 1995; 29(1):31.
26. Anderson R, Hanrahan SJ. Dancing in pain: pain appraisal and coping in dancers. *J Dance Med Sci*. 2008; 12(1):9–16.
27. McKewen K, Young K. Ballet and pain: reflections on a risk-dance culture. *Qual Res Sport Exerc Health*. 2011; 3(2):152–173. https:// doi.org/10.1080/2159676X.2011.572181.
28. Roussel N, De Kooning M, Schutt A, et al. Motor control and low back pain in dancers. *Int J Sports Med*. 2013; 34(2):138–43. https://doi.org/10.1055/s-0032-1321722.
29. Darlow B, Perry M, Mathieson F, et al. The development and exploratory analysis of the Back Pain Attitudes Questionnaire (Back-PAQ). *BMJ Open*. 2014; 4(5):e005251. https://doi.org/10.1136/bmjopen-2014-005251.
31. Goubert L, Crombez G, Hermans D, Vanderstraeten G. Implicit attitude towards pictures of back-stressing activities in pain-free subjects and patients with low back pain: an affective priming study. *Eur J Pain*. 2003; 7(1):33–42.
32. Greene Haas J. *Dance Anatomy*, 2nd ed. Human Kinetics; 2017.
33. Wang TJ, Russell JA. A tenuous pas de deux: examining university dancers' access to and satisfaction with healthcare delivery. *Med Probl Perform Art*. 2018; 33(2):111–117. https://doi.org/10.21091/mppa.2018.2018.
34. Leventhal H, Phillips LA, Burns E. The common-sense model of self-regulation (CSM): a dynamic framework for understanding illness self-management. *J Behav Med*. 2016; 39(6):935–946. https://doi.org/10.1007/s10865-016-9782-2.
35. Marras WS, Davis KG, Ferguson SA, et al. Spine loading characteristics of patients with low back pain compared with asymptomatic individuals. *Spine*. 2001; 26(23):2566–74. https://doi.org/10.1097/00007632-200112010-00009.
36. Buchbinder R, van Tulder M, Öberg B, et al. Low back pain: a call for action. *Lancet*. 2018; 391(10137):2384–2388. https://doi.org/10.1016/S0140-6736(18)30488-4.
37. Vibe Fersum K, O'Sullivan P, Skouen JS, et al. Efficacy of classification-based cognitive functional therapy in patients with non-specific chronic low back pain: a randomized controlled trial. *Eur J Pain*. 2013; 17(6):916–28. https://doi.org/10.1002/j.1532-2149.2012.00252.x.

Received 8-Nov-2018, accepted 6-Apr-2019
Published online 1-Sep-2019
https://doi.org/10.21091/mppa.2019.3025

Appendix P
Statement of Contribution

Curtin University

To Whom It May Concern:

For papers of joint authorship, the author attests to having completed the following aspects for each paper.

I, Danica HENDRY, contributed to conception, design, execution, data processing and analysis, and original manuscript writing and subsequent editing for the papers/ publications entitled:

1. Hendry, D., Chai, K., Campbell, A., Hopper, L., O'Sullivan, P. & Straker, L. (2020) Development of a human activity recognition system for ballet tasks. *Sports Med Open, 6*, 20
2. Hendry, D., Leadbetter R., Mckee, K., Hopper, L., Wild, C., O'Sullivan, P., Straker, L. & Campbell, A. (2020) An exploration of machine-learning estimation of ground reaction force from wearable sensor data. *Sensors, 20*(3), 740.
3. Hendry, D., Napier, K., Hosking, R., Chai, K., Davey, P., Hopper, L., Wild, C., O'Sullivan, P., Straker, L., & Campbell, A. (2021) Development of a machine learning model for the estimation of hip and lumbar angles in ballet dancers. *Med Probl Perform Art, 36*(2): 61-71
4. Chapter 6- Study 3: Movement quantity and quality: How do they relate to pain and disability in dancers?
5. Hendry, D., Straker, L., Campbell, A., Hopper, L., Tunks, R., & O'Sullivan, P. (2019). An exploration of pre-professional dancers' beliefs of the low back and dance-specific low back movements. *Med Probl Perform Art, 34*(3), 147-153.

Signature Redacted

Danica Hendry Date: 11th August 2021

I, Amity Campbell, as co-author, endorse that this level of contribution by the candidate indicated above is appropriate

Signature Redacted

Amity Campbell Date: 11th August 2021

1 of 1

CRICOS Provider Code 00301J

Curtin University

To Whom It May Concern:

For papers of joint authorship, the author attests to having completed the following aspects for each paper.

I, Danica HENDRY, contributed to conception, design, execution, data processing and analysis, and original manuscript writing and subsequent editing for the papers/ publications entitled:

1. Hendry, D., Chai, K., Campbell, A., Hopper, L., O'Sullivan, P. & Straker, L. (2020) Development of a human activity recognition system for ballet tasks. *Sports Med Open, 6*, 20
2. Hendry, D., Leadbetter R., Mckee, K., Hopper, L., Wild, C., O'Sullivan, P., Straker, L. & Campbell, A. (2020) An exploration of machine-learning estimation of ground reaction force from wearable sensor data. *Sensors, 20*(3), 740.
3. Hendry, D., Napier, K., Hosking, R., Chai, K., Davey, P., Hopper, L., Wild, C., O'Sullivan, P., Straker, L., & Campbell, A. (2021) Development of a machine learning model for the estimation of hip and lumbar angles in ballet dancers. *Med Probl Perform Art, 36*(2): 61-71
4. Chapter 6- Study 3: Movement quantity and quality: How do they relate to pain and disability in dancers?
5. Hendry, D., Straker, L., Campbell, A., Hopper, L., Tunks, R., & O'Sullivan, P. (2019). An exploration of pre-professional dancers' beliefs of the low back and dance-specific low back movements. *Med Probl Perform Art, 34*(3), 147-153.

Signature Redacted

Danica Hendry Date: 11th August 2021

I, Leon Straker, as co-author, endorse that this level of contribution by the candidate indicated above is appropriate

Signature Redacted

Leon Straker Date: 12th August 2021

1 of 1

CRICOS Provider Code 00301J

To Whom It May Concern:

For papers of joint authorship, the author attests to having completed the following aspects for each paper.

I, Danica HENDRY, contributed to conception, design, execution, data processing and analysis, and original manuscript writing and subsequent editing for the papers/ publications entitled:

1. Hendry, D., Chai, K., Campbell, A., Hopper, L., O'Sullivan, P. & Straker, L. (2020) Development of a human activity recognition system for ballet tasks. *Sports Med Open, 6*, 20
2. Hendry, D., Leadbetter R., Mckee, K., Hopper, L., Wild, C., O'Sullivan, P., Straker, L. & Campbell, A. (2020) An exploration of machine-learning estimation of ground reaction force from wearable sensor data. *Sensors, 20*(3), 740.
3. Hendry, D., Napier, K., Hosking, R., Chai, K., Davey, P., Hopper, L., Wild, C., O'Sullivan, P., Straker, L., & Campbell, A. (2021) Development of a machine learning model for the estimation of hip and lumbar angles in ballet dancers. *Med Probl Perform Art, 36*(2): 61-71
4. Chapter 6- Study 3: Movement quantity and quality: How do they relate to pain and disability in dancers?
5. Hendry, D., Straker, L., Campbell, A., Hopper, L., Tunks, R., & O'Sullivan, P. (2019). An exploration of pre-professional dancers' beliefs of the low back and dance-specific low back movements. *Med Probl Perform Art, 34*(3), 147-153.

Signature Redacted

Danica Hendry Date: 11th August 2021

I, Peter O'Sullivan, as co-author, endorse that this level of contribution by the candidate indicated above is appropriate

Signature Redacted

Peter O'Sullivan Date:25.8.21

Curtin University

To Whom It May Concern:

For papers of joint authorship, the author attests to having completed the following aspects for each paper.

I, Danica HENDRY, contributed to conception, design, execution, data processing and analysis, and original manuscript writing and subsequent editing for the papers/ publications entitled:

1. Hendry, D., Napier, K., Hosking, R., Chai, K., Davey, P., Hopper, L., Wild, C., O'Sullivan, P., Straker, L., & Campbell, A. (2021) Development of a machine learning model for the estimation of hip and lumbar angles in ballet dancers. *Med Probl Perform Art, 36*(2): 61-71

Signature Redacted

Danica Hendry Date: 11th August 2021

I, Kathryn Napier, as co-author, endorse that this level of contribution by the candidate indicated above is appropriate

Signature Redacted

Kathryn Napier Date: 11/08/2021

1 of 1

CRICOS Provider Code 00301J

Curtin University

To Whom It May Concern:

For papers of joint authorship, the author attests to having completed the following aspects for each paper.

I, Danica HENDRY, contributed to conception, design, execution, data processing and analysis, and original manuscript writing and subsequent editing for the papers/ publications entitled:

1. Hendry, D., Napier, K., Hosking, R., Chai, K., Davey, P., Hopper, L., Wild, C., O'Sullivan, P., Straker, L., & Campbell, A. (2021) Development of a machine learning model for the estimation of hip and lumbar angles in ballet dancers. *Med Probl Perform Art, 36*(2): 61-71

Signature Redacted

Danica Hendry Date: 11th August 2021

I, Paul Davey, as co-author, endorse that this level of contribution by the candidate indicated above is appropriate

Signature Redacted

Paul Davey Date: 11th August 2021

1 of 1

CRICOS Provider Code 00301J

To Whom It May Concern:

For papers of joint authorship, the author attests to having completed the following aspects for each paper.

I, Danica HENDRY, contributed to conception, design, execution, data processing and analysis, and original manuscript writing and subsequent editing for the papers/ publications entitled:

1. Hendry, D., Leadbetter R., Mckee, K., Hopper, L., Wild, C., O'Sullivan, P., Straker, L. & Campbell, A. (2020) An exploration of machine-learning estimation of ground reaction force from wearable sensor data. *Sensors, 20*(3), 740.

Signature Redacted

Danica Hendry Date: 11th August 2021

I, Ryan Leadbetter, as co-author, endorse that this level of contribution by the candidate indicated above is appropriate

Signature Redacted

Ryan Leadbetter Date: 23rd August 2021

1 of 1

Curtin University

To Whom It May Concern:

For papers of joint authorship, the author attests to having completed the following aspects for each paper.

I, Danica HENDRY, contributed to conception, design, execution, data processing and analysis, and original manuscript writing and subsequent editing for the papers/ publications entitled:

1. Hendry, D., Chai, K., Campbell, A., Hopper, L., O'Sullivan, P. & Straker, L. (2020) Development of a human activity recognition system for ballet tasks. *Sports Med Open, 6*, 20
2. Hendry, D., Napier, K., Hosking, R., Chai, K., Davey, P., Hopper, L., Wild, C., O'Sullivan, P., Straker, L., & Campbell, A. (2021) Development of a machine learning model for the estimation of hip and lumbar angles in ballet dancers. *Med Probl Perform Art, 36*(2): 61-71

Signature Redacted

Danica Hendry Date: 11th August 2021

I, Kevin Chai, as co-author, endorse that this level of contribution by the candidate indicated above is appropriate

Signature Redacted

Kevin Chai Date: 11th August 2021

Curtin University

To Whom It May Concern:

For papers of joint authorship, the author attests to having completed the following aspects for each paper.

I, Danica HENDRY, contributed to conception, design, execution, data processing and analysis, and original manuscript writing and subsequent editing for the papers/ publications entitled:

1. Hendry, D., Napier, K., Hosking, R., Chai, K., Davey, P., Hopper, L., Wild, C., O'Sullivan, P., Straker, L., & Campbell, A. (2021) Development of a machine learning model for the estimation of hip and lumbar angles in ballet dancers. *Med Probl Perform Art, 36*(2): 61-71

Signature Redacted

Danica Hendry Date: 11th August 2021

I, Richard Hosking, as co-author, endorse that this level of contribution by the candidate indicated above is appropriate

Signature Redacted

Richard Hosking Date: 12th August 2021

1 of 1

CRICOS Provider Code 00301J

Curtin University

To Whom It May Concern:

For papers of joint authorship, the author attests to having completed the following aspects for each paper.

I, Danica HENDRY, contributed to conception, design, execution, data processing and analysis, and original manuscript writing and subsequent editing for the papers/ publications entitled:

1. Hendry, D., Chai, K., Campbell, A., Hopper, L., O'Sullivan, P. & Straker, L. (2020) Development of a human activity recognition system for ballet tasks. *Sports Med Open, 6*, 20
2. Hendry, D., Leadbetter R., Mckee, K., Hopper, L., Wild, C., O'Sullivan, P., Straker, L. & Campbell, A. (2020) An exploration of machine-learning estimation of ground reaction force from wearable sensor data. *Sensors, 20*(3), 740.
3. Hendry, D., Napier, K., Hosking, R., Chai, K., Davey, P., Hopper, L., Wild, C., O'Sullivan, P., Straker, L., & Campbell, A. (2021) Development of a machine learning model for the estimation of hip and lumbar angles in ballet dancers. *Med Probl Perform Art, 36*(2): 61-71
4. Chapter 6- Study 3: Movement quantity and quality: How do they relate to pain and disability in dancers?
5. Hendry, D., Straker, L., Campbell, A., Hopper, L., Tunks, R., & O'Sullivan, P. (2019). An exploration of pre-professional dancers' beliefs of the low back and dance-specific low back movements. *Med Probl Perform Art, 34*(3), 147-153.

Signature Redacted

Danica Hendry Date: 11th August 2021

I, Luke Hopper, as co-author, endorse that this level of contribution by the candidate indicated above is appropriate

Signature Redacted

Luke Hopper Date: 16/08/2021

Curtin University

To Whom It May Concern:

For papers of joint authorship, the author attests to having completed the following aspects for each paper.

I, Danica HENDRY, contributed to conception, design, execution, data processing and analysis, and original manuscript writing and subsequent editing for the papers/ publications entitled:

1. Chapter 6- Study 3: Movement quantity and quality: How do they relate to pain and disability in dancers?

Signature Redacted

Danica Hendry Date: 11th August 2021

Signature Redacted

Anne Smith Date: 11th August 2021

I, Anne Smith, as co-author, endorse that this level of contribution by the candidate indicated above is appropriate

____

Anne Smith Date:

1 of 1

CRICOS Provider Code 00301J

Curtin University

To Whom It May Concern:

For papers of joint authorship, the author attests to having completed the following aspects for each paper.

I, Danica HENDRY, contributed to conception, design, execution, data processing and analysis, and original manuscript writing and subsequent editing for the papers/ publications entitled:

1. Hendry, D., Leadbetter R., Mckee, K., Hopper, L., Wild, C., O'Sullivan, P., Straker, L. & Campbell, A. (2020) An exploration of machine-learning estimation of ground reaction force from wearable sensor data. *Sensors, 20*(3), 740.
2. Hendry, D., Napier, K., Hosking, R., Chai, K., Davey, P., Hopper, L., Wild, C., O'Sullivan, P., Straker, L., & Campbell, A. (2021) Development of a machine learning model for the estimation of hip and lumbar angles in ballet dancers. *Med Probl Perform Art, 36*(2): 61-71

Signature Redacted

Danica Hendry Date: 11th August 2021

I, Catherine Wild, as co-author, endorse that this level of contribution by the candidate indicated above is appropriate

Signature Redacted

Catherine Wild Date: 16/08/2021

1 of 1

CRICOS Provider Code 00301J

Curtin University

To Whom It May Concern:

For papers of joint authorship, the author attests to having completed the following aspects for each paper.

I, Danica HENDRY, contributed to conception, design, execution, data processing and analysis, and original manuscript writing and subsequent editing for the papers/ publications entitled:

1. **Hendry, D., Straker, L., Campbell, A., Hopper, L., Tunks, R., & O'Sullivan, P. (2019). An exploration of pre-professional dancers' beliefs of the low back and dance-specific low back movements. *Med Probl Perform Art, 34*(3), 147-153.**

Signature Redacted

Danica Hendry **Date: 11th August 2021**

I, Rhianna Tunks, as co-author, endorse that this level of contribution by the candidate indicated above is appropriate

Signature Redacted

Rhianna Tunks **Date:** 11th August 2021

Appendix Q
Copyright Permission

24/08/2021 Mail - Danica Hendry - Outlook

Re: Request to use article for PhD thesis - Ticket ID [#5786557]

Open Research Support <orsupport@springernature.com>
Thu 8/19/2021 9:39 AM
To: Danica Hendry <danica.hendry@postgrad.curtin.edu.au>

Dear Dr. Hendry,

Thank you for contacting Springer Nature.

Copyright on any research article in open access (OA) journals published by Springer Nature is retained by the author(s). Authors grant Springer Nature a license to publish the article and identify itself as the original publisher. Authors also grant any third party the right to use the article freely as long as its integrity is maintained and its original authors, citation details and publisher are identified.

OA articles in Springer Nature journals are predominantly published under Creative Commons Attribution v4.0 International licence (CC BY). For more information please read our journal policy.

If you have any questions, please do not hesitate to contact us quoting your Ticket ID [#5786557].

With kind regards,
--
Rolando Libradilla
Global Open Research Support Specialist
Author Service

Springer Nature Group
www.springernature.com
--
Visit Springer Nature Support for answers to our most frequently asked questions.
--
Every day around the globe, our imprints, books, journals, platforms and technology solutions reach millions of people – opening the doors to discovery for our communities by enabling them to access, trust and make sense of the latest research, so that they can improve outcomes, make progress, and benefit the generations that follow.
--
In the Americas: Springer Nature Customer Service Center LLC, 200 Hudson Street, Suite 503, Jersey City, NJ 07311, USA
Registered Agent: Corporation Service Company, 251 Little Falls Drive, Wilmington, DE 19808, USA
State of Incorporation: Delaware, Reg. No. 4538065
Outside the Americas: Springer Nature Customer Service Center GmbH, Tiergartenstraße 15 – 17, 69121 Heidelberg, Germany
Registered Office: Heidelberg | Amtsgericht Mannheim, HRB 336546
Managing Directors: Martin Mos, Dr. Ulrich Vest, Franciscus Vrancken Peeters

> On Thu, 19 Aug at 2:35 AM , Danica Hendry <danica.hendry@postgrad.curtin.edu.au> wrote:
>
> > To Whom It May Concern
> >
> > I am writing to request for copyright permission of my published article with Sports Medicine Open (whereby I am the first author), to be included as chapters in my PhD thesis, currently being completed at Curtin University in Perth, Western Australia. The specific articles I would like copyright permission for are:
> >
> > Hendry, D., Chai, K., Campbell, A., Hopper, L., O'Sullivan, P. & Straker, L. (2020) Development of a human activity recognition system for ballet tasks. *Sports Med Open*, *6*, 20
> >
> > I am carrying out this research in my own right, and have no association with any commercial organisation.

https://outlook.office.com/mail/inbox/id/AAQkAGVmYWRiZjNiLTkwYWMtNGZhYi1iZTlmLTg3ZThiOWZlMjQwZQAQAAjRboCXMvBPi54syZp%2FKD… 1/2

I need to submit my PhD thesis very soon, thus hope you can expedite my request. I would be grateful for your consent to the copying and communication of the work as proposed.

Thank you for the consideration of this request, and I look forward to hearing from you soon.

Kind Regards

Danica Hendry

Re: Request to use article for PhD thesis

Sensors <sensors@mdpi.com>
Thu 8/19/2021 4:47 PM
To: Danica Hendry <danica.hendry@postgrad.curtin.edu.au>
Cc: sensors@mdpi.com <sensors@mdpi.com>

Dear Danica,

Thank you very much for your email. Please note that Sensors is an open access journal and we follow the conditions of the Creative Commons Attribution license (http://creativecommons.org/licenses/by/4.0/), which provides that published material can be re-used without obtaining permission as long as a correct citation to the original publication is given.

If you would like to cite several parts of this publication, please directly contact the authors. The copyrights belong to you for current status.

Hope this does help. Feel free to let me know if you have any other questions.

Kind regards,
Jayleen Chen
Managing Editor

On 2021/8/19 9:32, Danica Hendry wrote:
>> To Whom It May Concern
>>
>> I am writing to request for copyright permission of my published
>> article with Sensors (whereby I am the first author), to be included
>> as chapters in my PhD thesis, currently being completed at Curtin
>> University in Perth, Western Australia. The specific articles I would
>> like copyright permission for are:
>>
>>
>> Hendry, D., Leadbetter R., Mckee, K., Hopper, L., Wild, C.,
>> O'Sullivan, P., Straker, L. & Campbell, A. (2020) An exploration of
>> machine-learning estimation of ground reaction force from wearable
>> sensor data. /Sensors, 20/(3), 740.
>>
>>
>> I am carrying out this research in my own right, and have no
>> association with any commercial organisation.
>>
>>
>>
>> I need to submit my PhD thesis very soon, thus hope you can expedite
>> my request. I would be grateful for your consent to the copying and
>> communication of the work as proposed.
>>
>>
>>
>> Thank you for the consideration of this request, and I look forward to
>> hearing from you soon.
>>

>>
>>
>> Kind Regards
>>
>>
>>
>> Danica Hendry
>>
> *
> *
>
>

24/08/2021 Mail - Danica Hendry - Outlook

Re: Request to use articles for PhD Thesis

M Bokulich <bokulich@sciandmed.com>
Thu 8/19/2021 11:42 PM
To: Danica Hendry <danica.hendry@postgrad.curtin.edu.au>

Dear Danica,
Any format would be acceptable. Please let me know if there are any other questions.
--
Best wishes,
M. Bokulich
Science & Medicine

T 610-660-9187
bokulich@sciandmed.com

From: Danica Hendry <danica.hendry@postgrad.curtin.edu.au>
Date: Wednesday, August 18, 2021 at 9:29 PM
To: M Bokulich <bokulich@sciandmed.com>
Subject: Re: Request to use articles for PhD Thesis

Dear Mr Bokulich

Pertaining to the email below, I would just like to confirm that it is ok if rather than posting the articles as pdfs within my dissertation, that I present the articles in the thesis formatted in style with the rest of my dissertation.

Many thanks

Danica

From: Danica Hendry
Sent: Wednesday, August 18, 2021 5:43 AM
To: M Bokulich <bokulich@sciandmed.com>
Subject: Re: Request to use articles for PhD Thesis

Dear Mr Bokulich

Many thanks for your speedy and comprehensive response.

Regards
Danica

On 17 Aug 2021, at 11:45 pm, M Bokulich <bokulich@sciandmed.com> wrote:

> Date: Aug 17, 2021
>
> Dear Danica:
>
> Congratulations on finishing your thesis!
>
> The letter below grants permission to post the PDFs of your two papers as part of your dissertation in the Curtin University repository. The 12-month embargo is also waived for the second paper. Please let me know if there are any questions.

https://outlook.office.com/mail/inbox/id/AAQkAGVmYWRiZjNiLTkwYWMtNGZhYi1iZTlmLTg3ZThiOWZlMjQwZQAQAJtYFtsSao5IldIHjp9tFHE%3D 1/3

24/08/2021 Mail - Danica Hendry - Outlook

Permission requested for:
Material: full paper, pdf version
From: Hendry, D., Straker, L., Campbell, A., Hopper, L., Tunks, R., & O'Sullivan, P.
Article Title: An exploration of pre-professional dancers' beliefs of the low back and dance-specific low back movements.
Publication: *Med Probl Perform Art,* 2019;34(3):147-153.
DOI: https://doi.org/10.21091/mppa.2019.3025

Material: full paper, pdf version
From: Hendry, D., Napier, K., Hosking, R., Chai, K., Davey, P., Hopper, L., Wild, C., O'Sullivan, P., Straker, L., & Campbell, A.
Article Title: Development of a machine learning model for the estimation of hip and lumbar angles in ballet dancers.
Publication: Med Probl Perform Art 2021;36(2):61-71.
DOI: https://doi.org/10.21091/mppa.2021.2009

Proposed Use:
Type: Dissertation, e-depository
Title: --
Authors: Hendry D
Journal/Book: --
Publisher/University: Curtin University, Perth, Australia
Pub Date: 2021
License period: indefinite

Thank you for your note requesting permission to reproduce/excerpt material from MPPA.

As per your e-mail dated August 17, 2021, we hereby grant you permission to reproduce the aforementioned material in print and electronic format subject to the following conditions:

1. Use is limited to one-time only in the current edition of the dissertation/publication and electronic editions of that publication (not derivatives) and is for educational purposes only.

2. Credit to the source is given to the original publication, with full reference given either in figure legend and/or reference list.

3. This permission is granted for non-exclusive world rights.

4. This permission does not include the right to grant others permission to re-use or reproduce this material in other formats or publications (except for versions made by non-profit organizations for use by the blind or handicapped persons).

5. A fee of $ 0.00 is paid to the publisher.

6. For material posted in dissertations/university archives, the standard 12-month embargo on posting is waived and use of the final PDF in the dissertation/archives is granted.

Thank you for publishing in MPPA.
--
Best wishes,
Mike Bokulich
Editor/Publisher
MPPA

tel 610-660-9187
bokulich@sciandmed.com

https://outlook.office.com/mail/inbox/id/AAQkAGVmYWRiZjNiLTkwYWMtNGZhYi1iZTlmLTg3ZThiOWZlMjQwZQAQAJtYFtsSao5IldIHjp9tFHE%3D 2/3

24/08/2021 Mail - Danica Hendry - Outlook

Science & Medicine
PO Box 313
Narberth PA 19072
USA

From: Danica Hendry <danica.hendry@postgrad.curtin.edu.au>
Date: Tuesday, August 17, 2021 at 1:50 AM
To: M Bokulich <bokulich@sciandmed.com>
Subject: Request to use articles for PhD Thesis

Dear Mr Bokulich

I am writing to request for copyright permission for two of my published articles with MPPA (whereby I am the first author), to be included as chapters in my PhD thesis, currently being completed at Curtin University in Perth, Western Australia. The specific articles I would like copyright permission for are:

Hendry, D., Straker, L., Campbell, A., Hopper, L., Tunks, R., & O'Sullivan, P. (2019). An exploration of pre-professional dancers' beliefs of the low back and dance-specific low back movements. *Med Probl Perform Art, 34*(3), 147-153.

Hendry, D., Napier, K., Hosking, R., Chai, K., Davey, P., Hopper, L., Wild, C., O'Sullivan, P., Straker, L., & Campbell, A. (2021) Development of a machine learning model for the estimation of hip and lumbar angles in ballet dancers. *Med Probl Perform Art, 36*(2): 61-71

I am carrying out this research in my own right, and have no association with any commercial organisation.

I need to submit my PhD thesis very soon, thus hope you can expedite my request. I would be grateful for your consent to the copying and communication of the work as proposed.

Thank you for the consideration of this request, and I look forward to hearing from you soon.

Kind Regards

Danica Hendry

https://outlook.office.com/mail/inbox/id/AAQkAGVmYWRiZjNiLTkwYWMtNGZhYi1iZTlmLTg3ZThiOWZlMjQwZQAQAJtYFtsSao5IldIHjp9tFHE%3D 3/3